Title: A real-time demand response pricing model for the smart grid

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A Real-Time Demand Response Pricing Model for the Smart Grid

By

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Declaration

I, ASM Ashraf Mahmud, declare that "this dissertation is my own unaided research. It is being submitted for Doctor of Philosophy (PhD) degree at the University of Bedfordshire, UK. This thesis has not been submitted before for any degree or examination in any other educational establishment, except where appropriate acknowledgement (or reference) is made in the thesis."

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Signature:

Date:

Abstract

This thesis contributes to a novel model for Real-Time Price Suggestions (RTPS) of the Smart Grid (SG), which is the next generation modern bi-directional grid, particularly with respect to the pricing model. The research employs an experiment-based methodology which includes the use of a simulation technique. The research developed a Demand Response (DR) pricing model. Energy users are keen to reduce their bills, and Energy Providers (EP) is also keen on reducing their industrial costs. The DR model would benefit them both. The model has been tested with the UK-based traditional price value using real-time usage data. Energy users significantly reduced their bill and EP reduced their industrial cost due to load shifting. The Price Control Unit (PCU) and Price Suggestion Unit (PSU) utilise a set of embedded algorithms to vary price based upon demand.

This model makes suggestions based on an energy threshold and makes use of Simultaneous Perturbation Stochastic Approximation Methods to produce prices. The results show that bill and peak load reductions benefit both the energy provider and users. The tests on a daily basis and monthly basis both benefit energy users and energy provider. The model has been validated by building a hardware prototype. This model also addresses users' preferences; if users are non-responsive, they can still reduce their bills. The model contributes significantly to the existing models, and the novel contribution is the PSU which uniquely benefits energy users and provider. Therefore, there is a number of fundamental aspect of contributions to the model RTPS constitutes the final thesis of the PhD. The Real-Time Pricing is a better pricing system, algorithm developed on a daily basis and monthly basis and finally building a hardware prototype.

Keywords – Smart Grid, real-time, price, demand response, stochastic process, user preference, Peak-to-Average Ratio, Price Suggestion Unit, PSU

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List of Abbreviations

2TP	2 Tier Pricing
ACO	Ant Colony Optimisation
AMI	Advance Metering Infrastructure
AS	Ancillary Services
ASM	Ancillary Service Market
CMP	Capacity Market Program
CPP	Critical Peak Pricing
DA-RTP	Real-Time Price
DB	Demand Bidding
DDSM	Decentralised Demand Side Management
DG	Demand Grid
DLC	Direct Load Control
DPAMU	Malicious Users and Unstable Energy Providers
DR	Demand Response
DSM	Demand Side Management
EA	Evolutionary Algorithm
ECC	Energy Consumption Controller
ECS	Energy Consumption Scheduling
EDRP	Emergency DR Program
EEGI	European Electricity Grid Initiative
EP	Energy Provider
FDPS	Finite-Difference Price Selection
FDSA	Finite-Difference Stochastic Approximation
GA	Genetic Algorithm
GHG	Green House Gas
HEM	Home Energy Management
IBR	Inclined Block Rate
IDSS	Intelligent Decision Support Systems
IEA	International Energy Agency
IEI	Institute for Electric Innovation
iHEM	in-Home Energy Management
IoT	Internet of Things
KKT	Karush–Kuhn–Tucker
M2M	Machine-to-Machine
MC	Monte Carlo simulation
MG	Micro Grid
MILP	Mixed-Integer Linear Programming

MIP	Mechanism of Identification and Processing
NLP	Non-Linear Programming
OECD	Organisation for Economic Co-operation and Development
OSGi	Open Services Gateway initiative
PEV	Plug-in Electric Vehicle
PHEV	Plug-in-Hybrid Electric Vehicle
PLP	Peak Load Pricing Day Ahead
PLP	Peak Load Pricing
PMSC	Power Market Scheduling Centre
PSO	Particle Swarm Optimisation
PTR	Peak Time Rebate
PV	Photovoltaic
RTP	Real-Time Pricing
RTPS	Real-Time Price Suggestion
SA	Simulated Annealing
SAPC	Annealing-based Price Control
SE	Stackelberg Equilibrium
SG	Smart Grid
SOAP	Simple Object Access Protocol
SPPS	Simultaneous Perturbation Price Selection
SPSA	Simultaneous Perturbation Stochastic Approximation
SRA	Strategic Research Agenda
SSU	System Simulation Unit
STB	Set Box
TOU	Time-of-Use
V2G	Vehicle-to-Grid
VPP	Variable Peak Pricing
WT	Wind Turbine

Dedication

This thesis is dedicated to my wonderful family, in particular for my wife who has sacrificed her time to uplift my motivation. This thesis is also dedicated to my late dad and mum who always encouraged me to start a PhD. I could not start my PhD when they were alive. Nevertheless, I started my PhD after their departure from this world. I pray and hope that they would always get a reward from Allah (SWT). May Allah grant them the highest place in paradise.

Acknowledgement

This is the moment I would like to thank Allah (SWT) who enabled me to complete my thesis. I am so much grateful to him. Without his endless mercies, it would not be possible to complete this thesis. He always showered mercies during my study.

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List of Publications

The following publications from part of the work contributing to this thesis.

Published	Year
Mahmud AA, Sant, P (2018): The Novel Real-Time Price Suggestions (RTPS) model for the Smart Grid via Stochastic Approximation. Submitted to IET Smart Grid, It is in the review stage.	2018
Mahmud AA, Sant, P (2018): Real-Time Price Suggestion through Stochastic approximation in the Smart Grid, presentation in 2018 the 6th IEEE International Conference on Smart Energy Grid Engineering (SEGE), University of Ontario Institute of Technology (UOIT), Oshawa, Ontario, Canada.	2018
A Real-Time monthly DR Price system for the Smart Energy Grid (2017) ASM Ashraf Mahmud, Paul Sant, Faisal Tariq, David Jazani, EAI Endorsed Transactions on Energy Web 17(13): e3 4 (13), 1-11, Available at http://eudl.eu/doi/10.4108/eai.3-8-2017.152981	2017
Real-time price savings through price suggestions for the smart grid demand response model, (2017) ASM Ashraf Mahmud, Paul Sant, Smart Grid and Cities Congress and Fair (ICSG), 2017 5th International, Istanbul, Available at http://ieeexplore.ieee.org/abstract/document/7947603/	2017
Empirical analysis of Real-Time pricing mechanisms for demand-side management: contemporary review, (2016) ASM Ashraf Mahmud, Paul Sant, Faisal Tariq, David Jazani, Future Generation Communication Technologies (FGCT), UK, Available at http://ieeexplore.ieee.org/abstract/document/7605071/	2016

1 Introduction

1.1 Current Scenario of the Smart Energy Grid

1.1.1 Energy consumption trends

In the past few decades [1], technological development has produced an innumerable collection of commodities to make our daily lives more convenient and comfortable. The population has more than doubled over the last hundred years. The current increasing world population has led to an exponential growth [2] in energy consumption and is estimated as 7,413,329,843 by mid-2016. Energy usage has increased fourfold, and researchers also predict that automobiles will consume energy ten times faster than population growth. The principal energy sources such as coal, gas and nuclear power are often linked to a corresponding detrimental effect upon the environment and global climate. By the estimation of the International Energy Agency (IEA), 70% of energy production [2] comes from fossil fuels, especially from coal (42%) and gas (21%). This energy is responsible for 40% of anthropogenic carbon dioxide and other greenhouse gas emissions (CO_2e).

In 1820, Michael Faraday discovered electromagnetic induction and that electricity is a process of transformation of different types of energy into electricity. Various sources of energy are available including water, wind, solar or fossil fuel. According to the Shift Project [3], overall estimated (existing) energy is generated from hydropower (17%), nuclear (11%) and oil (4%) in addition to the most popular sources, coal (40%) and natural gas (23%). Integration of more clean and renewable energy sources is the ultimate solution as fossil fuels have been exhausted and we have to find a better way of managing the world's energy needs. This is the very important focus in the energy arena because of high energy demand for the fast growth of the world population.

Gradually, people are moving towards cleaner energy and new cleaner sources; renewable energy sources are being sought as expedient solutions for the future supply of diversified energy with wind, wave and solar power being the most representative examples. Different countries have different trends for production of electricity. For example, renewable electricity in the UK currently produces 15% of overall demand, and it is growing at a fast rate [4].

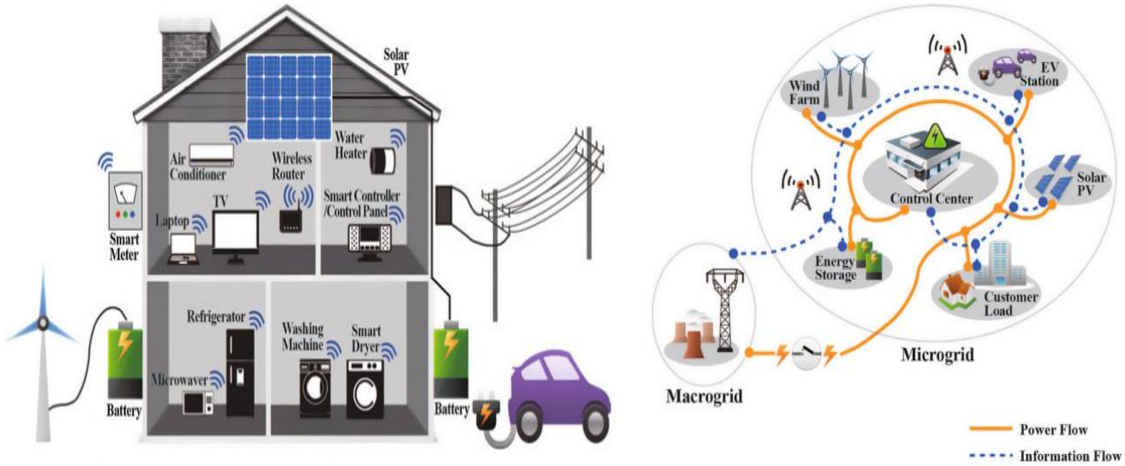


Figure 1: Future Smart Home and Microgrid that is part and parcel of SG [5]

1.1.2 Emergence of microgrids

An effect of this diversification of energy sources is that electricity distribution systems will become a hybrid framework combining the traditional large-scale grid with emerging microgrids of renewable energy. Over the last decade, energy saving measures have been addressed, especially in the residential sector. The Smart Micro Grid (SMG) [6]–[7] infrastructure is a solution that would allow customers to produce energy from renewable sources and the wider customer base use surplus energy. However, such a system should have a local distribution centre, and a user can play a vital role in using renewable energy. Some researchers have already suggested using a different architecture for residential and in-Home Energy Management (iHEM) [6] systems to achieve cost savings. The figure 1 shows the microgrid is also a part of the SG.

According to Hamilton and Gulhar [8] by 2050, there will be a vision for energy appliances with downloadable energy from appliance manufacturers that nobody could have imagined in the 1980s. People will be able to pull energy from appliances with integrated virtual energy aggregators. Through this virtual energy aggregator, people can share energy throughout their neighbourhood by accessing social media. Some of the technology comes with the smart home: automation in all aspects is the future vision, like sockets, light, air-conditioning, appliances that will respond to various price signals where a customer does not need to intervene.

1.1.3 Power Grid to Smart Grid (SG)

Currently, the power grid is a traditional grid, which is used for electricity generation, transmission, distribution and control. It is unidirectional, transmitting power from generators to customers. In most developed countries, the electricity grid was developed more than 50 years ago and is becoming outdated.

Using the current power grid, the USA could not avoid a major power cut in 2003; almost 50 million people were left without power for two days [5]. Hurricane Sandy caused an environmental disaster in Atlantic Ocean coast, and 6 million people were without power for two days. Such examples demonstrate the need for smarter and more effective ways of energy generation and management.

To increase the efficiency of electricity production, there is a need to modernise the grid. In the twenty-first century, the power grid is referred to as the SG, which distributes energy in an automated fashion. Day by day demand for electricity is increasing. Therefore, the SG is the ultimate solution to reduce power load, decrease the carbon footprint and make the whole power network more reliable and secure.

An SG is a bi-directional electricity network that can intelligently integrate the actions of all users connected to it in order to deliver electricity that is both sustainable and economically viable. It is the next generation power distribution network, which applies technologies and tools for bringing intelligence and dynamic consumer interactivity to the power grid [9].

According to the National Institute of Standards and Technology report [10], Smart Grids (SG) can enhance services. SG works in better way for power reliability, optimising facility utilisation, extending energy distribution capacity, managing disruption, auto response in system disturbance, deployment facility of renewable energy sources, integrating dispense power sources, automatic operation and maintenance, greenhouse gas emissions reduction , peak load reduction, grid security, Plug-in-Electric Vehicles (PEV), new energy storage choices and extended consumer choice.

In the SG, there are two paradigms, namely Vehicle-to-Grid (V2G) systems [11] and microgrids [12]. To provide energy and ancillary services, electric V2G is being used to transfer discharging energy back to the grid. That can also be achieved through bi-directional power flows by changing the rate of modulation [11],[13]–[14]. For decentralisation of electricity, microgrids coordinate energy resources, storage devices and loads. A microgrid can manage demand, supply, voltage and frequency of the electricity [15]. In a microgrid, the connected operational mode uses the same policy which has historically been used in the main grid, but in island mode, it can control faults and voltages [16] independently.

Energy is sometimes generated from a small-scale power generator like solar photovoltaic (PV) or a small-level wind turbine which can be from 3kW to 10MW [11]. These are defined as small-scale grids which provide advantages to Energy users. However, these small-scale grids can be accommodated into an SG. An SG can communicate and manage the small-scale grids in an efficient way. It can be connected to the closest power station or connected to a home where we can refer to it as a microgrid with a smart home. To reduce dependency on fossil fuel and make our life more sustainable, we must diversify the energy sources either in small scale or large scale.

It is important that more dissemination of small-scale Demand Grid (DG) of renewable energy may reduce the burning of coal and gas and control Green House Gas (GHG) emission. To enhance power reliability and quality, a DG-based power distributed power grid may help a lot in the case of main power grid failure. The distributed nature of generating electricity would create space for a resilient electricity market. In that case, a dynamic pricing solution would assist a lot in the SG. Moreover, the weather is a challenge to create demand and supply of electricity where DG can play an important role. However, managing this SG is not an easy task, and this has become a growing research area.

We are currently facing challenges of global climate change, increasing carbon dioxide emission/greenhouse gas emission and an ever-increasing demand for electricity. We are very fortunate that we can face those challenges by using information technology. An SG would be a by-product of IT. SG will be the future generation grid which can successfully address all of the challenges. The Internet of Things (IoT) will be very helpful in terms of machine learning for demand and pricing management. Sensors will assist the SG to communicate with all appliances that are used within the home.

People will be able to obtain the real-time information that is necessary for them. The SG will be a powerful management tool for managing renewable energy as it can respond quickly in the case of a power blackout. It is a complex power system which can achieve efficient and sustainable clean energy. However, it will not be possible to develop that kind of infrastructure without proper planning from the government.

The SG would prove very beneficial for the modern generation. In that intelligent grid, smart meter or sensor-based elements would be deployed in which security would be an issue. Energy storage is another very important issue which is in demand. In that scenario, energy storage will play a vital role in energy management. However, EP would be able to communicate with energy users on a real-time basis and control competitive markets by using this intelligent and bi-directional communication infrastructure. Figure 2 shows the concept of the future bi-directional SG.

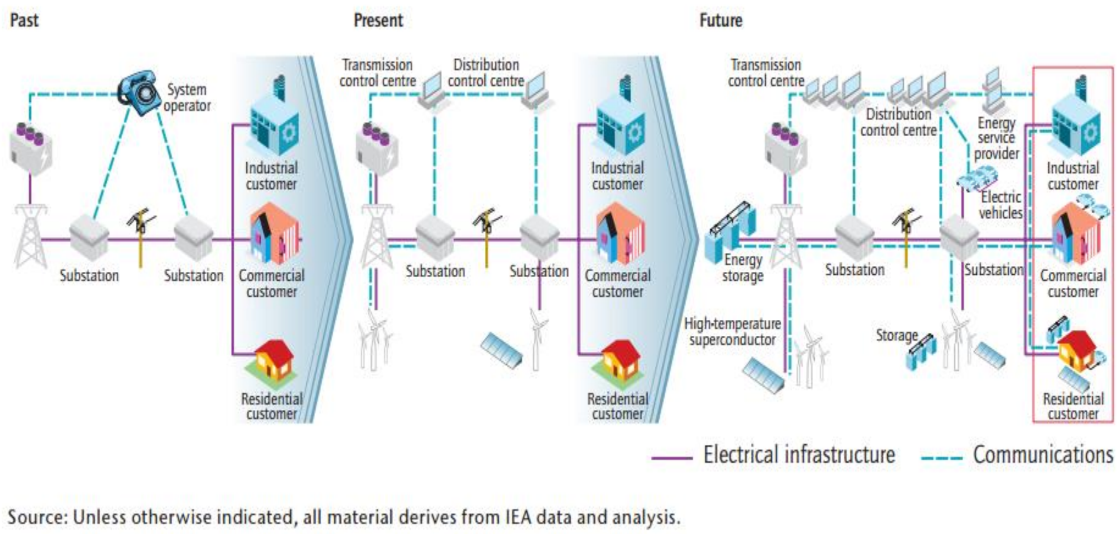


Figure 2: **Overview of SG regarding current power grid [17]**

To ensure higher efficiency, sharing information is important. Figure 2 shows how this would be a realistic model in the futuristic SG. Any failure in the user side power distribution would lead to error messages being generated thus providing immediate updates on the EP's side so that they can address that failure on a real-time basis. The SG can be connected to many subsystems which would enable better assistance for the SG.

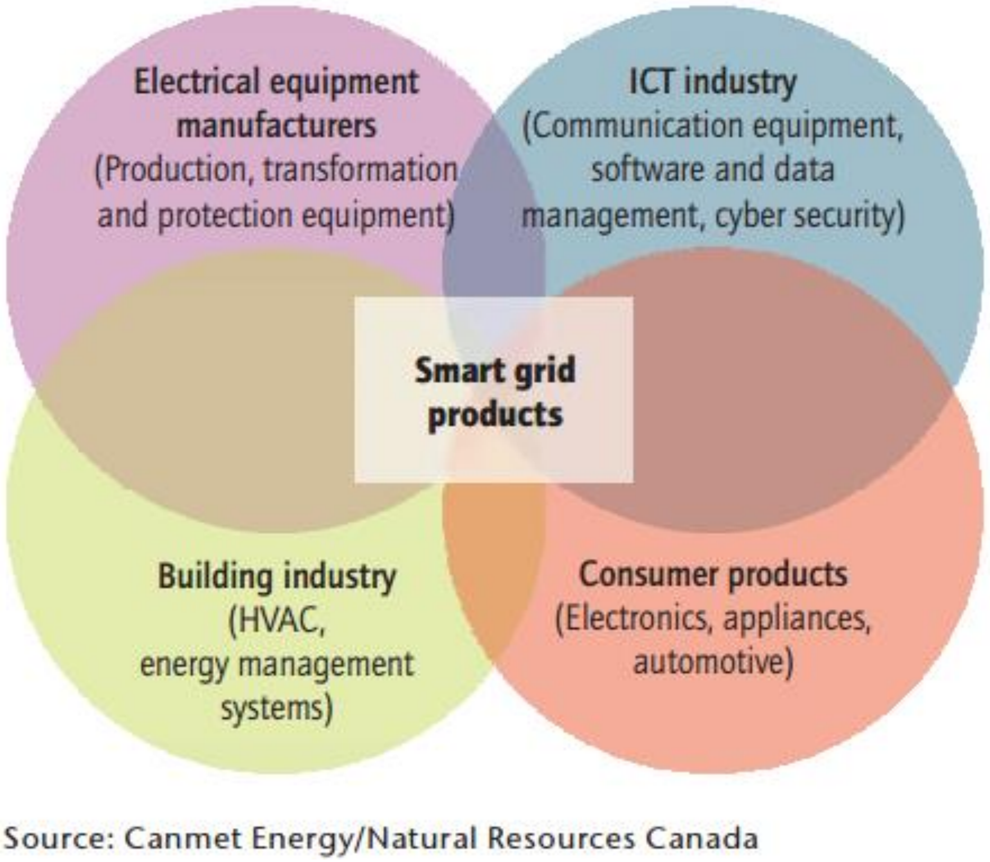
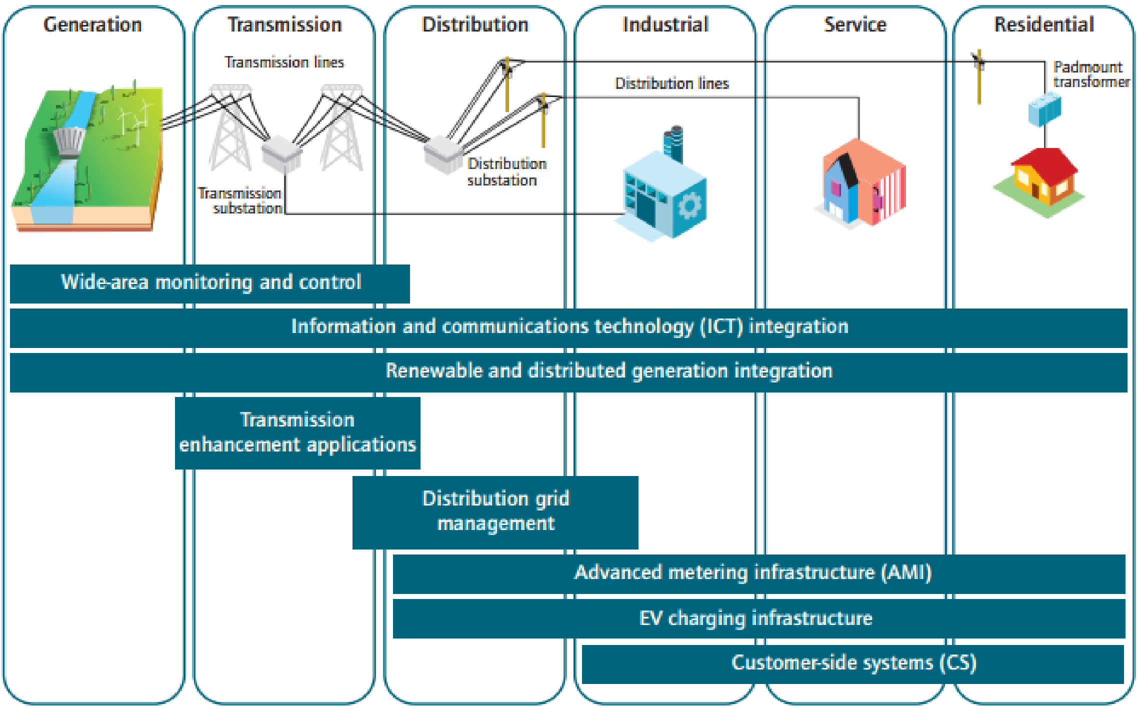


Figure 3: **SG product provider**

This is a new area, and so research is in progress, and the definitive shape of SG is not yet fully clear. However, a roadmap has been produced, and the direction of travel is clear. The SG products road map shows in figure 3. Different countries have different directions. However, all of them are principally trying to achieve similar goals. The USA has the highest priority on reducing GHG as 10 million barrels of petroleum are consumed by everyday vehicles. China is addressing green energy solutions because of environmental pollution. To implement SG infrastructure, there are several infrastructure products involved in which SG can run in a better way, as ICT would provide software and communication equipment, electrical manufacturers would provide transformation, the building industry can provide Heating, ventilation, and air conditioning (HVAC), and consumer industry can provide smart appliances.

Different aspects of the SG, e.g. generation, transmission, distribution and retail, have a variety of technologies adopted from generation to end users. Figure 4 shows some of the technologies that are involved in the SG.



Source: Technology categories and descriptions adapted from NETL, 2010 and NIST, 2010.

Figure 4: Technology involved in SG [17]

The SG has developed based on information technology where controlling, monitoring, analytics and the decision-making process involving wired and wireless communication systems. The IoT would be very helpful because of sensor-based facilities and the ability to gather and collect information in real time. Figure 5 shows that the future SG architecture.

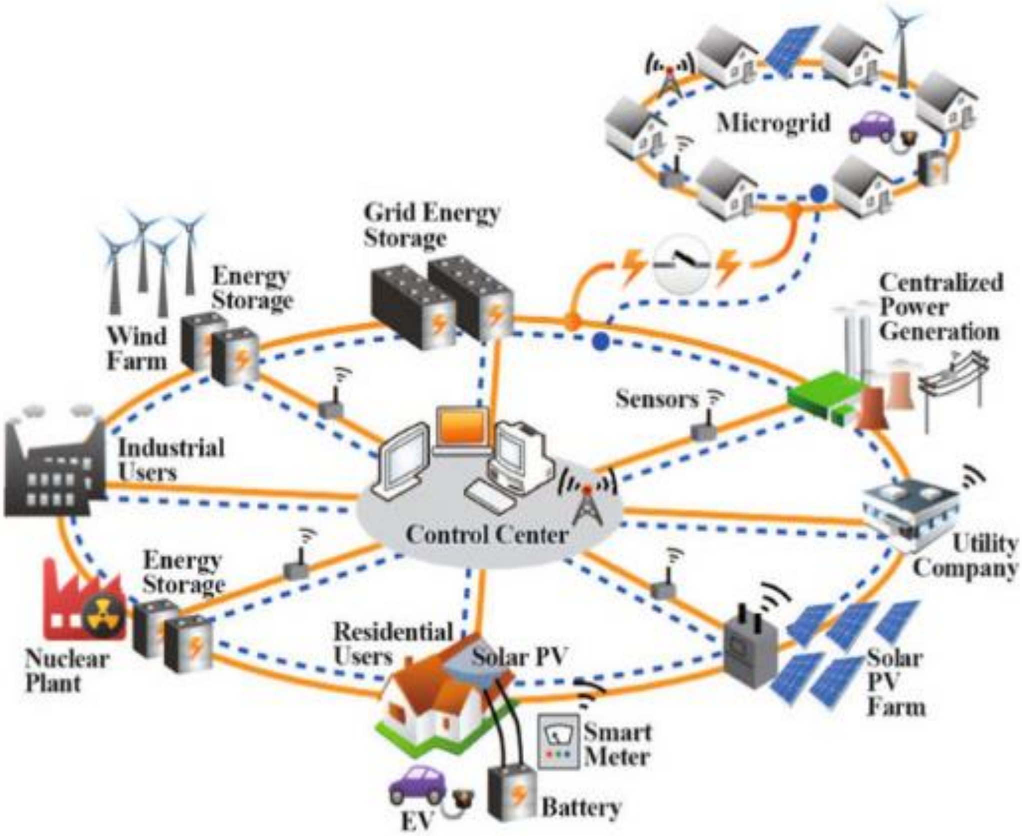


Figure 5: **The future of SG** [5]

Smart power generation is the key issue in SG infrastructure because it should be compatible with the underlying distribution system. Managing all the subdivision of SG components is vital, and IT is assisting in that aspect. Regarding developing an application for managing the demand and pricing, security and reliability are important to control demand and response.

In that scenario, developing an underlying pricing algorithm is the fundamental development of the SG, and much research is being devoted to it. Our area of work concerns developing that core and fundamental component of SG. Without a managing application, SG would not be able to communicate with the Microgrid (MG) or even smaller-scale Demand Grid (DG).

The current power grid consists of a power plant to produce electricity and transmit electricity with high voltage to a distribution centre, and at the end, the users receive their electricity from the distribution centre. The power plant infrastructure is normally located in a densely populated area so that it can transmit easily through a transformer to the distribution centre.

The flow of electricity, DC or AC, is used in different scenarios. A steady electron stream flows from the transmission site and before distribution, its voltage is further downregulated and distributed in the substation. At the service, level voltage is maintained to deliver electricity to a user. So, it is difficult to predict for the SG whether this infrastructure would be changing or not. Currently, the SG works on the basis of this infrastructure rather than developing new infrastructure. Regarding bi-directional communication, it demands some changes, but it is highly unlikely to be changed in a quick manner as a huge investment would be involved for the country.

Such an approach would lead to problems such as identifying the requirement of changes from current grid to smart and its solution in developing countries is highly crucial because of their ageing infrastructure, growing demands, generation and regulation variations. The growing need for a number of renewable energy sources and electric vehicles is a significant problem regarding security and low carbon emission issues in place. SG meets these challenges to deliver energy in an efficient, affordable and sustainable way.

Changes in ageing infrastructures could affect security, stability and reliability. The demand for electricity from fossil fuel would lead to intensifying the concern about carbon emissions more than double by 2050 [17]. Implementing the political statement like the G8 request is also a challenge on infrastructure. The International Energy Agency (IEA) launched roadmaps that aim to deliver energy from generation to end users on a real-time basis in the SG. However, new SG infrastructure should be implemented strategically as the old infrastructure developed over a hundred years would gradually need huge investment to maintain quality.

The Organisation for Economic Co-operation and Development (OECD) countries are trying to change their infrastructure as energy demand grows like China has comparatively invested more and has a newer distribution and transmission infrastructure than other OECD countries in the European, North American and Pacific regions. Europe has ageing transmission and distribution lines that are proportionately higher number than other regions.

Recent investment in the Pacific region has given a new dimension of infrastructure like Japan invested pointedly in its transmission: Yokohama City is one of the examples. The USA invested in deploying phasor measurement units on a transmission system that are providing a lot of required and reliable information on old infrastructure. A phasor is like other sensor devices, and with advanced metering infrastructure (AMI) are key components for the SG. It enables a two-way flow of data, price signals, able to collect, store and report information to Energy users; it can organise user load, location, meter problems, loss, theft; and retail providers may be able to maintain their accounts.

One of the key things is that SG should be implemented gradually without interrupting the daily operation of energy with the current grid. This kind of challenge can not detract us from SG rather the opportunity benefits us a lot. Nonetheless, all types of challenges would need to be overcome to implement SG. The government needs very consistent regulations, plans and investment. The important thing is the public should be engaged and educated about the benefits offered by SG. More significantly, research and financial organisations should work together to achieve SG for future clean energy.

1.1.4 SG is a key element of the Smart City

Cities [18] have been the driving force of economic growth since the industrial revolution. Recently, "smart cities" are introducing a smart driverless car that consumes energy to make the environment clean. In many countries, the revolution has increased development, but not necessarily addressed the smart approach of the city. Figure 6 shows the SG and others are the part and parcel of the Smart Cities.

Figure 6: Smart city should connect to various smart lifestyles [5]

By using technology, some cities are accumulating data, delivering innovation, and enhancing the lives of citizens. Juniper Research recently compiled its list of the top five [19] smart cities. The study focuses on sustainability and efficiency that are two predominant benefits of smart cities. Five essential components are identified for a smart city: technologies, buildings, energy, transportation and road infrastructure, and the smart city itself. People like comforts in this era of globalisation. To fulfil the dream of a smart city, energy management must be smart, and the SG delivers that solution.

Historically, a city was always counted as a symbol of civilisation. In modern history, a smart city would be a powerful tool to define civilisation. We are in an information technology-driven age, and a smart city is a vital component of it. The SG is one of the most vital components of the smart city. However, defining a smart city, we have to consider all other components of a smart city such as smart governance, smart business, smart transport and so on and so forth.

1.2 Where to improve on the current system state

It is right to say that the current power grid needs a lot of improvement in various areas; the pricing system is one of the areas where we concentrate. In a bi-directional grid, Energy users and providers both should not be deprived on any occasion of technological advancement. We have chosen to concentrate on researching to improve this area. Every one of us wants to save on the cost of energy; either from the EP's or energy users' sides. It is a matter of demand and response between them. We will thoroughly cover demand response and pricing methods the way energy providers charge Energy users and how we can make a balance and reduce the cost of both sides. Currently, the EP charges on a flat-rate basis which is unfair to Energy users. Our research will strike a balance between them and propose a solution to it.

1.3 Thesis organisation

Other than the introduction to the thesis, we discuss the literature review with the rationale in Chapter 2. We discuss methodology in Chapter 3. We give the distinct idea of our proposed work in Chapter 4. We discuss the analysis and result in Chapter 5, and finally, we discuss the conclusion in Chapter 6. The rest of the thesis is organised with references and appendices.

1.4 Thesis planning and implementation

The thesis plan and implementation started in November 2014. Over the three years journey, we have completed the work for developing the Demand Response pricing algorithm. The design and diagrammatic work plan are given below:

Time Table	Nov 14 to Feb 15	Mar 15 to 15 July 15	15 July 15 to Sep 15	Oct 15 to Dec 15	Jan 16 to Mar 16	Apr 16 to June 16	Aug 16 to Dec 16	Jan 16 to Jan 18
A literature review of finding out gaps of the works in the field of Demand Response modelling.								
Documentation for Progression Point 1								
Implementation of existing algorithms								
Proposing new algorithm for Price Suggestion Unit (PSU)								
Testing New algorithm for Price Suggestion Unit (PSU)								
Documentation for Progression Point 2								
Paper Publishing and conference								
Testing with actual data								
Final thesis writings								

2 Literature Review

2.1 Introduction

The SG is the key element of a Smart City which is the most important aspect of a country. Now, the question is how SG benefits its stakeholders and how it can be implemented. In this context, the end user would play a vital role in the implementation of SG. It is not an easy task as it is a tough transformation from the current grid infrastructure to SG. Nonetheless, it is important to implement the SG in the most effective and efficient way. The right things to do which are effective and to do the things right which is efficient, both would demand research in the SG. Most researchers are concentrating on how the SG can be implemented in their country in the most effective and efficient way. Most countries are assessing the difficulties of implementing SG, as it is modern technology. A significant number of research works are already in place in the SG arena.

The key element of the SG is the demand response, and the end user would be a key player in the demand response system. Enhancing the current grid infrastructure and engaging the end users might help to handle the complexity of the grid system management. There are several ways of handling the instability of electricity prices. Some research is in place on this issue. Researchers have concentrated on this issue and emphasised this to end users who are the key component to enhance system stability and balance between demand and supply. Demand Response (DR) is the reliable strategy for the SG.

This thesis focuses on the benefits of both energy management and the Energy Users' (EU) side. A recent literature review is discussed here in the perspective of an energy management system in the SG context in association with the Demand Response model. Considering a grid with and without the participation of end users in the DR, our model has been proposed. There are several models discussed in this thesis so that finding gaps would be easier. Discussed are current pricing methods, Demand and Response discussion, challenges, the potential of other proposed systems: to find out the research gaps.

2.2 Discussion on Demand Response model

2.2.1 The current state of demand for electricity

As energy demand is increasing tremendously in developing economies, energy providers have to increase their capacity to meet peak demand. Energy cannot be stored due to the high cost of doing so. Currently, the power grids' energy production has not been fully utilised; almost 70% of their energy is wasted [20]. There is a significant difference between average and peak demand. Energy providers must, therefore, produce energy to meet peak demand not average demand because of the unidirectional flow of energy. Now, the huge challenge is to generate a system that can provide a balance between energy demand and supply [21]. This is very complicated for many countries in the world.

2.2.2 Evolution of the Demand Response (DR) programme

In the SG, Demand Response (DR) is a key feature [22],[23]. To achieve the benefits of the EP and customers, a Demand Response model concept has evolved to ensure advantages are exploited. This is very significant for SG deployment. DR terminology is being used as a tariff in the US Department of Energy and is proving attractive to customers [24],[25]. Efficient DR programming design is very important in the SG [26].

A Demand Response model is used for reducing the power consumption so that energy providers and customers benefit, mutually. Peak demands could be reduced [27] by triggering expensive-to-run power plants and, as a result, this enables energy providers to address their pollution obligations [28]. Some Demand Response programmes are identified and presented in a graphical format in figure 7 [29].

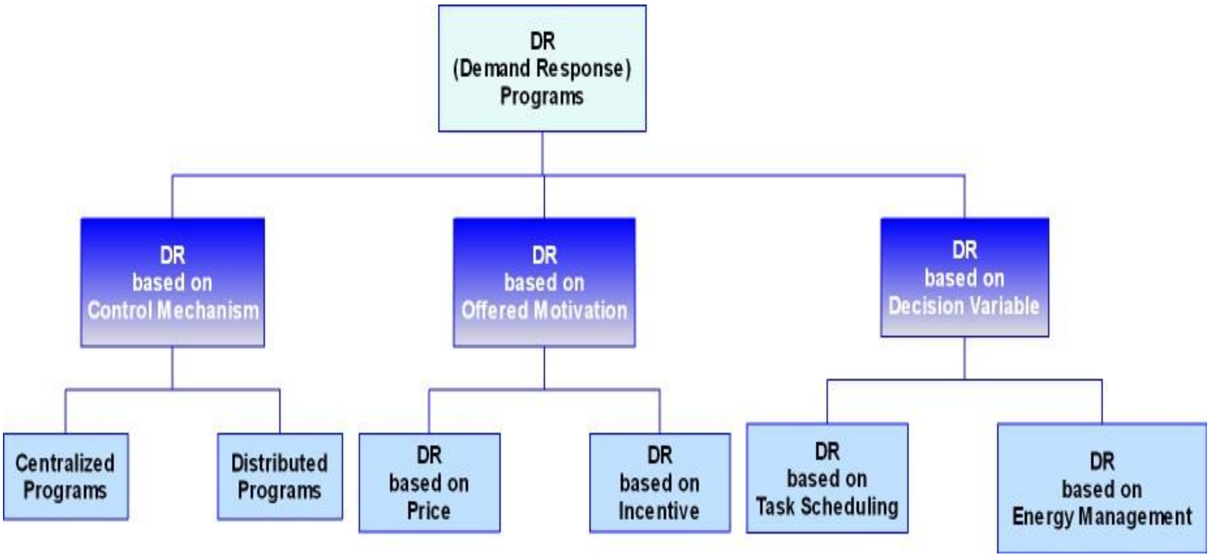


Figure 7: Some of the classifications of DR programmes [7]

As the SG is bi-directional, it can manage Demand Response. However, electricity supply by customers demand is complex. There are many Demand Response programmes established based on different parameter sets. Figure 7 shows that three major DR programmes based on control mechanism, offered motivation and decision variable are practised in the Smart Grid. However, our DR approach is on price based offered motivation.

2.2.3 Control mechanism DR

In this type of DR, a controlling grid is performed in a centralized manner that is difficult to implement in a large grid. Alternatively, there is another further classification of the control mechanism: a distribution program [30],[31] that assists to transmit price signals to local distribution centres. In this type of DR, users can interact with each other to reduce their aggregate load. Such an approach ensures scalability. In this distributed manner, consumers can react to the system if it is critical. On the other hand, DR schemes are monitored and coordinated by a central controller using a centralised programme. This approach is being used in island microgrids whose main function is the preservation of power balance independently. The distribution system is important to accommodate multiple energy sources to relocate energy within the different distribution centres, and local power consumption wind turbines (WTs) can be used for that purpose.

Reducing the aggregate load in the distribution management system and taking real-time [32] decisions can improve the reliability of the system [33]. A DR system can take security issues [34] regarding personal identity which is collected by smart meters into consideration [35] and the reduction of loads to unload transmission lines to prevent an emergency condition arising [36]. To change the usage behaviour [37], DR systems can encourage customers to contribute to the programme through incentives.

Fuel cells that are a type of energy discharger of distributed power sources can play a role in distributed management DR. They can be produced from electrochemical reactions. They are not just used on an emergency basis, but rather they are used as a continuous power generator. They can reduce congestion on the energy grid, prevent power cuts and reduce prices of electricity.

2.2.4 Offered motivation DR

Considering motivation, customers are offered incentives, and they are asked to respond to the system to shift their power demand in this DR approach. This could be based on time variance or incentive-based. Offered incentives have a key impact on customers' habits [38]. The cost of electricity at different times are defined as for a price-based DR. Incentive-based Demand Response was studied in [39]. It was shown that customer response is significant as the mean consumption of both research-purpose selected groups are almost the same in the distribution grids [40] [41] [42].

2.2.5 Decision variable DR

DR groups are deciding for activation of the requested loads and amount of energy allocation [43]. There are two types of DR programs available: (i) task-scheduling (ii) and energy management based. Task-scheduling concerns activation time of requests of loads of non-flexible devices (i.e. must run) like a refrigerator or flexible loads like a water heater or Plug-in Hybrid Electric Vehicle (PHEV) [44],[45] to reduce the power consumption at peak demand. Energy management based DR [46] aims to reduce the energy usage of specific loads to reduce total loads from peak loads [47].

This research primarily focused on a price-based approach; however, considering all of the processes of DR, it can extend to a hybrid approach to DR management. It can consider one process; moreover, it can take also a hybrid approach, if necessary from control mechanism based DR, distributed manner, from motivation-based DR, price-based approach, and from decision-based DR, the management-based approach would be better to implement a Real-Time Price (RTP) model.

2.3 Difference between DR and DSM

Time-based price changes from the energy provider instigate the energy users to change their energy usage behaviour can be called as DR. It is a program to provide the opportunity for energy users who are taking part of reducing the overall peak load in the power grid. Primarily, this program is used by energy provider to keep a balance between demand and supply of the electricity. DR offers various pricing methods to attract energy users to participate in the program. DR is also a kind of important option for the energy industry because of its modern approach. Economic benefit, the welfare of the customers as well as the reliability of the power plant by reducing the peak load would be the main purpose of the DR program.

A Demand Side Management (DSM) strategy is proposed by Gelazanskas and Gamage [48]. Energy efficiency is the primary goal of the DSM. These two methods are different but provide a smart solution for the energy usages. DSM refers to the concept that energy users can use energy efficient products that can reduce electricity usages, it also means that users can reduce their electricity demand. However, energy users can be influenced by energy provider to reduce their energy usages in the peak time that can be referred to as DR.

2.4 Discussion of pricing methods

It is important not only to consider a DR mechanism to develop a model but also to look at pricing methods. In DR management, varieties of pricing methods have been implemented. Apparently, diverse pricing methods [29] are found in various research works, especially on flat price, Time-of-Use (TOU), Inclined Block Rate (IBR), different types of peak pricing like Critical Peak Pricing (CPP), Variable Peak Pricing (VPP), Peak Load Pricing (PLP), Day-Ahead Real-Time Price (DA-RTP) and Real-Time Price (RTP) bases. However, time-varying prices are involved with incentive-based programmes.

2.4.1 Time-of-Use (TOU)

Time-of-Use (TOU) is the application of flat pricing; it is a traditional energy pricing system, and it is in building customers' minds. TOU reserves a flat price within different periods: a study [49] described in one piece of research demonstrated that without incentive customers did not respond and even with incentive customers' responses are not significant. Time-of-Use (TOU) electricity pricing is implemented where they will be charged for peak hours. Utilities did not place any clear incentive for the customers to reduce their bills. To change, customer behaviour, the clear incentive might help them use less power or less expensive power.

Comparing 50 places [50] for Ontario's Time-of-Use (TOU), they found that proper TOU pricing was with the approach of single peak pattern in summer and dual peak pattern in winter. They suggested relocating solar/wind generation costs, and that on/off-peak length should be four hours; this price should be exercised in the summertime, and its scheme should be split into two in a day considering customer responsiveness and implementation cost. Customers are categorised [51] as industrial, commercial or residential but not based on responsiveness, and time-varying prices are based on the energy price. In the UK, Economy 7 is also a pricing tariff which is an expensive rate that usually runs from 7 am to midnight, and the cheaper, off-peak rate runs from midnight to 7 am, though this varies with the meter. Economy 7 is often called a Time-of-Use (TOU) tariff because payment depends on the times of energy usages.

Economy 7 is cheaper for those who use energy mostly at night, such as for storage heaters, hot water tanks etc. It is off-peak night time discounted for 7 hours tariff although it varies in summertime and wintertime, where summertime is 2 am to 9 am, and wintertime is from 1 am to 8 am. However, one of the difficulties is that heating water or storage heaters at night might not last into the next day. Without good planning ahead, it is difficult for users to maintain this timetable. For example, to use domestic appliances like a washing machine or dishwasher at night, a time awareness device is required to act on it. Daytime use of Economy 7 can be double the rate, which is very inconvenient for users.

2.4.2 Peak Load Based Price

There are hours identified by energy providers as peak, mid-peak, off-peak etc. based on aggregate consumptions and each group has different rates in Time-of-Use Pricing (TOU). Based on this maximum demand Peak Pricing (PP) has been used by many utility companies for large industrial loads. The aggregate of the peak, off-peak or mid-peak load is considered. Critical Peak Pricing (CPP) is also being considered for industrial consumers. It might be 200 times higher than the base rate in the particular coincident hour. CPP is a type of pricing method which has similarities with TOU pricing. Some reduction of energy usages [39] is achieved in CPP by users who respond to the price signals from energy providers.

Case studies in Europe and China [52],[53] show information tools are important for the customer to participate in DR programmes; it is not just price incentives and proving smart equipment to the clients for their compliments. To create awareness and implement proper tools are very important when implementing a pricing model in DR. There is a survey [54] based on several case studies of various dynamic pricing programmes that demonstrate the need for appropriate tools to be available. Customers could be motivated to reduce their bills, but the survey shows that a few customers did respond in peak time or did not shift their loads until incentives were offered.

Moreover, in a time of system stress, customers receive different new prices which are unexpected. These are not electronically efficient pricing systems, anyway. Variable Peak Pricing (VPP), Peak Time Rebates (PTR) or Peak Load Pricing (PLP) are introduced where only peak price matters. It is measured based on average energy consumption. It is based on the feedback from the customers due to high price and customer satisfaction was not guaranteed.

2.4.3 Inclined Block Rate (IBR)

Consumers' monthly, daily or hourly load beyond a threshold are considered in Inclining Block Rates (IBR) [55] and based on consumer price increases to a higher value (if load exceeded) of the marginal price. This influences consumers to keep their load below a certain level at certain times. IBR is practised by the Clatskanie Public

Utility for residential users [56] and by Alabama Power for industrial consumers [57]. However, TOU pricing method is the most used method in the USA.

2.4.4 Incentive-based pricing

Incentive-based DR customers are required to respond to incentives to reduce their bills. The customer's response is voluntary, but sometimes customers are penalised because of failing to meet their contract. Their contract is based on TOU or flat rate, but incentive was given to them to respond, but they could not respond, and eventually, sometimes they received a larger bill than the previous bill. Direct Load Control (DLC) is where it is possible to remotely turn off appliances of customers; Interruptible/Curtailable (I/C) load is where open incentives are provided for customers to curtail specific loads and customers who do not respond to this option could receive penalties. Besides these, additionally offered motivation programmes include Emergency DR Programme (EDRP), Capacity Market Programme (CMP), Demand Bidding Programme (DB) and Ancillary Service Market (ASM), which were effective in a different perspective. To reduce peak demand, they found the usefulness of DR schemes studied in [29] based on offering motivations.

	Residential	Commercial	Industrial
TOU	✓ ✓	✓ ✓	✓ ✓
CPP	✓ ✓ ✓	✓ ✓ ✓	✓ ✓
PLP	✓ ✓ ✓	✓ ✓	✓ ✓
PDR	✓ ✓	✓ ✓ ✓	✓ ✓ ✓
RTP	✓ ✓ ✓	✓ ✓ ✓ ✓	✓ ✓ ✓ ✓
DLC	✓ ✓ ✓	✓ ✓	✓ ✓
I/C	✓ ✓	✓ ✓ ✓	✓ ✓ ✓ ✓
EDRP	✓	✓ ✓ ✓	✓ ✓ ✓
CMP	✓	✓ ✓ ✓	✓ ✓ ✓
DB	✓	✓ ✓ ✓	✓ ✓ ✓ ✓
ASM	✓	✓ ✓ ✓	✓ ✓ ✓

Figure 8: Regarding offered motivation, DR impacts on reducing the peak demand [39]

In Washington, DC, Pepco's customers reduced their bills by 20% using a Critical Peak Pricing (CPP) programme in the summer. Additional case studies presented in [58] show similar results. By providing real-time feedback in a home display board, in a pilot survey of Hydro One's in Ontario, Canada, it was shown that even without price incentives to RTP, customers achieved an average of 6.5% power reduction.

According to F. Wolak's experiment [39] on customer response to Real-Time Pricing, figure 8 shows that how offered motivation DR programme benefits to reduced peak demand in the Smart Grid. Our model considers a price based offered motivation DR, most of the pricing methods assist to reduce peak demand. However, RTP significantly contributes to reducing peak demand for all types of customers. Therefore, we have chosen RTP as our pricing method in our model.

2.4.5 Day-ahead Real-Time Pricing (DA-RTP)

One of the methods is a day-ahead Real-Time Pricing (RTP) model where a customer receives a 24-hour pricing forecast. The model [47] used an optimisation model for addressing users' energy demands and the capacity of various energy generators by using a distributed Lagrange Newton algorithm to find out locations of Marginal Prices to address distribution. However, it could not address users' behaviour to able to find the best scheme for customers.

Many utilities take Day-Ahead Pricing into account, and DAP can be calculated based on the clearing market prices and carry a separate price for each hour of the next day in the day-ahead market. Day-Ahead RTP (DA-RTP) is an alternative solution for RTP. Customers know their predictive price for the next day. Working with 320 customers in Ontario, Canada, with a test system showed that the DA-RTP scheme obtained higher load factors [59] and lower peak-to-peak distance ratios.

2.4.6 Real-Time Pricing (RTP) with current technology

RTP pricing has been practised by the Electric Reliability Council of Texas [60] for consumers. These prices are updated every 15 minutes (not on a real-time basis). RTPs are calculated only after-the-fact, and this can create uncertainties for consumers. RTP implemented on time basis, and the challenge is real-time communication between the EP and users, however, without considering users' responses, high customer satisfaction is not possible.

There is an RTP pricing algorithm [61] proposed in the digital-based SG where it is an assumption that customers are using an Energy Consumption Scheduling (ECS) device. The paper claims that aggregate load demand reduced in energy consumption by using a stochastic approach [62],[63]. It estimates scheduling demand to minimize the electricity payment of the users without considering their responsiveness. However, there is no comparison between traditional price and experimental price. Moreover, partial user engagement helps to shift the peak load to reduce PAR. It uses schedule-based appliances which are not fit for the current state of the SG. They did not consider the customers' preferences. To implement the model, every user must have scheduling smart devices to communicate their ECS, which is not possible for the current scenario in the world. We use the current state of real data in different buildings that are obtained from different appliances into our model. Our proposed novel RTPS model answered all of the hypothetical questions. Our model RTPS compared the traditional price and model price.

They used only customers' usages based on the fact that an optimised price may have been offered. However, customers who are keen on reducing their value and act on responding to receive a reduced optimised price. Users try to achieve a reduced energy price even with incentives [64],[65] and maximize social welfare [66], but there are some challenges of load synchronization [67] and price instability [68],[69]. The rationality of price changes for users is yet to be explored while the ECS device is in use. We use the current state of load synchronisation system. However, the marginal price [67] can be a solution for the load synchronisation problem by adjusting pricing tariffs with Inclining Block Rates (IBRs).

This research focuses on RTP as people aspire for ease and an instant decision-making system. RTP programmes for different customers such as residential, commercial and industrial were effective. There is a logical relationship between the EP and Energy user. An EP can control a user's consumption remotely. They use the price-based programme to consumers who can shift their consumption during the day [64] because the EP can use DLC and a price-based load control programme. Nonetheless, Real-Time Pricing (RTP) and Advanced Metering Infrastructure (AMI) [61] and smart meter can be used for Demand Response solutions. The proposed RTPS model is price-based DR which is perfectly fine for the customers. However, the model can be fine-tuned with hybrid DR approach which is price and incentive together.

2.5 Discussion of pricing challenges

From the above discussion, our model considers the Price-based DR and RT price. However, some other challenges need to be taken into account. Some of the challenges in pricing mechanism are discussed below.

2.5.1 Renewable energy

Renewable energy is itself challenged because of both the clients who have excess energy and the EP are supplying to the system to provide further clients. Real-time power generation is difficult for forecasting models to adjust to and forthcoming operation is also difficult [51] for the same reason. Customers sometimes manually respond to energy providers, which could be accommodated in the system. This can now be another focus of research.

There is a view to maximising the customers' surplus renewable energy [70] that can be extracted from early defined factors, by considering the suitability of the dynamic benefit function. However, customer happiness and satisfaction are not guaranteed as some of the customers are interested in ensuring their comfort and they are willing to pay for their full satisfaction, and some of them obviously want their bill reduced. Somehow, there is a balance of approach that is missing.

2.5.2 The distributed manner of the energy system

To integrate distributed energy resources, the Micro Grid plays an important [71] role for wind turbines, solar photovoltaic panels, and energy storage devices such as battery and distributed generation systems applied from the main SG. On an hourly basis, renewable sources can be distributed considering the solar and wind forecast.

Regarding an approach that uses a user preference concept [7] with distributed energy resources, a particle swarm optimisation technique has been used which is based on some appliances' energy scheduling tasks, and simple linear programming used in [72] for Real-Time Pricing (RTP) for load control. However, that work failed to address uncertainty. Some others have tried to solve domestic energy management problems in different ways by considering user interaction by using quasi-dynamic pricing [73] for the unit of energy consumed with a base price and penalty term. A model should address the balance between main and distributed local systems. The coordinated system or DLC system solves the issue in the SG. Our proposed RTPS is a system which directly communicates with the users and handles those issues as we are not using the scheduling devices.

2.5.3 Lack of energy generation

SG faces enormous challenges [74] that will increase by 2035. It has to fulfil energy demands during the nights while photovoltaic, solar power is not generating enough electricity in wintertime for unforeseen reasons. To achieve social welfare and benefits for the customer, only financial incentives might not be the option to encourage customers; it is a bit challenging due to their response to incentives during a dynamic implementation pricing [75] in the SG. Fair charging is sometimes an issue in TOU to minimize the total cost or peak load [76]. Coexistence and fair implementation [77] is also a challenging issue but clients may achieve the fair price with their enormous efforts. Our model addresses that issue, we have shown the fair charge is possible within the RTP framework.

2.5.4 Probabilistic behaviour

Concerning the implementation of pricing, the Demand Response model itself is challenging due to its probabilistic behaviour and the nature of data [29]. Reliable operation is also challenging to get Real-Time Pricing (RTP). Pricing decision making is not straightforward due to how real time has to be taken into account. For dynamic pricing, there can be either a central or local distribution centre, and the decision can be made either locally or centrally. We have used the probabilistic approach in our model so that we can handle the issue related to probability.

2.5.5 Baseline creation

Concerning efficient baseline creation, it is very challenging to bypass price formation in a wholesale market when customers need to understand demand control [78]. Price formation depends on infiltrating technology, a variety of demands, policies implemented by governments, fuel prices, and infrastructure costs of DR programmes [79]. Base price creation sometimes may be difficult for the EP as they need to depend on the marginal industry cost. Our technique of the model can accommodate those issues. Our model can address the issue with the continuous probabilistic manner of the algorithm introduced.

2.5.6 Load uncertainty

In Demand Response load uncertainty is a big challenge concerning pricing for the customer. There is a lack of a perfect knowledge of users' energy requirements in existing demand management algorithms. There is a need to know the statistical estimation of the future load demand. Currently, for that reason, Incline Block Rates (IBR) pricing systems are being introduced. The current state of TOU pricing cannot handle the issue as it is charging customers sometimes unfairly without knowing their certain load. Presumably, Real-Time Pricing (RTP) is significant and integrating it with IBR could address [80] the issue. In that respect, SG infrastructure is important as real-time bi-directional communication is necessary. Our model focused on RTP assuming that SG is in place.

2.5.7 Customer diversity

Customer categories [81] might have an impact on pricing policies (e.g. Time-of-Use rates) as industrial customers may respond for their benefit, and it might be difficult for residential customers to respond in the same manner. To promote and approve new technology like SG, political risks and opportunities are involved in new economic development and these might potentially cause price increases. Diverse customers' demand could have a potential impact on defining a unit price. In that regard, price segregation for different categorical customers could solve the problem. Our model can accommodate high or low customer demand; accordingly, it generates an optimised price.

2.5.8 Climate change

Providing electricity with climate change is challenging, where SG could provide adaptation to and mitigation of climate change [81] by escalating low-carbon electricity production. Centralised or decentralized energy systems, radical or incremental change, how climate change objectives can be integrated into the SG expansion, these are some of the issues. Furthermore, changing the current electricity system should be based on context and how it could be integrated with local, regional and national levels. The Smart Grid can mitigate the climate change issue as DR management could potentially contribute to resolving the issue.

2.5.9 CO_2 emission

Electricity production releases 41% of the world’s carbon dioxide and 26% of global greenhouse gas emissions [82] because of a high reliance on fossil fuels. To alleviate distinctive CO_2 by 2050, there needs to be an 80% reduction in greenhouse gas emission, according to the Intergovernmental Panel on Climate Change (IPCC) [83]. There is a projected increase of 70% in electricity production by 2035. Ultimately, the SG has wider appeal, and it is the solution for a more efficient, reliable, resilient and lower-carbon electricity system [84]. It appears to be a fact that the main goal of the electricity industry is a reliable supply and reasonable costs for customers [85]. Our model ensures the reasonable cost for the customers.

2.5.10 Users’ responsiveness concern

To minimise the Peak-to-Average Ratio (PAR) in the aggregate load demand through pricing, users need to respond; but it is difficult to get a response from users: some of the users respond, some of them do not. This algorithm does not need direct user interaction and uncertainty was not considered in [65] users’ price-responsiveness. A user sometimes does not respond because of lack of awareness [32].

There are some things that need to be taken into account like user behaviour, the time of day, climate conditions, and also the price of the electricity. There is a discussion on a user’s response in [86] and this is based on household or industrial users response to various price scenarios and is modelled through a utility function [87]. However, the work did not address the issue of optimisation of the user’s response and non-response together. Our model addresses the user responsiveness accommodating PSU.

2.5.11 Multiple energy sources concern

There is a lack of research on the integration of multiple energy providers and sources. Most of the research is based on a single energy source. By considering Real-Time Pricing (RTP), user responses and multiple energy sources, designing Demand Response models are complex. A study showing forecasting errors [88] of wind and solar energy demonstrates that these approaches suffer operational challenges as well as the uncertainty of power generation. Data generation using multiple energy sources in a micro-grid system [89] including wind power, solar PV, battery and natural gas is probabilistic. There are operational challenges because of the probabilistic nature of the data, for example, uncertain weather data for wind or solar power.

Furthermore, probability originates from any sort of uncertainty. In order to address uncertainties, a probabilistic method is a better approach. Consequently, there is a research conducted for “Forecasting and Probabilistic Methods for Power Systems: A Review of UK Research” [90]: it suggests that probabilistic methods manifest the underlying uncertainties better than deterministic approaches. The probabilistic approach is better in planning and operating SG systems. Hence, our model adapted probabilistic methods.

Decision making is of significant importance [91] and consequential as far as multiple energy sources are concerned. Clients respond to the core of the energy provider’s price announcement by shifting their energy load. One model of the Stackelberg game approach discussed using a bi-level programming model with two decision levels approached minimising the error, but it is difficult to derive an optimisation that is nested. One problem is embedded in another one. It cannot differentiate the problems between two; eventually, without any association, it cannot optimise two problems at the same time.

There is a scenario-based [92] approach using Monte Carlo (MC) simulation and using Mixed-Integer Linear Programming (MILP). MILP solvers solve the problems, but they do not consider complicated customer behaviour and that is very important for consideration. It may have stochastic data and might use Monte Carlo simulation to generate a sample, but the linear approach would not be effective because of the stochastic nature of the data. However, the real data which have the potential to achieve sound out-come into the research. Our model used real data to address the issues that are formulated.

Other research [93] addressed storage capacity and cost-saving in the event of rigid demands. It did not consider inflexible demands from customers and used an algorithm for renewable energy generation and did not address the customer’s social welfare. The algorithm did not integrate multiple sources, and such an approach is an important issue to be addressed. Our model addresses the issue.

2.6 Discussions of challenges of implementing the model in the SG

2.6.1 Discussion of electricity infrastructure challenges, particularly in smart meter

The changing electricity infrastructure would be an issue while transforming the current power grid to an SG. There are a number of projects running in Europe for the SG. There is some policy development whose objectives in 2020 anticipate that they need major transformation for their infrastructure [84]. Upgrading the current grid would be an important factor to address security and renewable energy generation. It is also important to develop ICT-integrated energy substations. Renewable energy sources, secure supply, augmented customer priority in the current market would be the priority for Europe. Building infrastructure is also important for the SG by deploying assets and infrastructure system building. Socially and psychologically acceptable intangible elements with new policy would play a vital role in the SG.

The transition from the current state of the power grid to the SG is not an easy task. It should be targeted as a long-term task. Vision with policy could lead in that direction. Market research and deployment would assist progress. There is a dire need to explore investment potential to implement the SG. There is some research, e.g. the Joint Research Centre for energy, which tries to develop a framework for the European SG Task Force [94]. Their work aims to set a direction of moving Smart Energy sectors by analysing almost 300 projects for investment, motivation, system integration and contribution to EU energy policy goals. They also address issues relating to data protection and security regarding infrastructure; a key suggestion of their work is to suggest deploying smart meters and Advance Metering Infrastructure that is very much in line with our research. This is closely aligned, in terms of our approach to our work.

Our model also suggests considering smart meters because they have been widely adopted around the globe; most governments deploy smart meters to users so that bi-directional communication can be established in the SG technology. Application of the Assessment Framework for Energy Infrastructure Projects of Common Interest in the field of Smart Grids [95] Group 4 explored how the communication infrastructure should integrate new sensors and actuators on the medium voltage (MV) grid into demand-side management (DSM) and the use of an automatic fault tolerance system.

According to Pike Research [96], European investment is approximately €56.5 billion in the SG, and they have already deployed 240 million smart meters across the whole of Europe. According to the International Energy Agency (IEA) [97], they require €1.5 trillion investment to transform the Power Grid into the SG. The required investments for the USA would be $338 to $476 billion over 20 years. Also, according to [97], $1.5 trillion is required by 2030 to transform the SG. According to the State Grid Corporation of China (SGCC), they need $600 billion by 2020 to transform their infrastructure from the traditional grid to the SG.

China is planning to deploy 360 million smart meters by 2030. South Korea is planning to invest $24 billion over the next 20 years, and they have already invested $824 million in the SG. They deployed 500,000 smart meters in 2010, 750,000 smart meters in 2011 and a predicted 24 million smart meters by 2020. Australia [98] invested $360 million for the SG in 2010. They are committed to developing the Smart City and spending almost AUS$74.6 million. The Australian state of Victoria had rolled out 2.4 million smart meters by 2013. In 2010, Japan invested $849 million for Smart Grids [99]. According to Bloomberg News, Japan is addressing the issue of the nuclear crisis at Fukushima [100]. India's distribution losses are huge, in some of the places they are losing 62% of the distribution, where energy theft is also included. They are losing an average of 50% of the distribution regarding non-technical loss [101]. They are planning to deploy 130 million smart meters by 2020. Brazil invested $240 million in the Smart Grid [99]; they are going to deploy 63 million smart meters by 2021.

From the above discussion, we would like to conclude that developed countries realise to invest in the SG, in particular in smart meters, as the only way out for combating the future energy crisis. Our model adopted the smart meter as part of our architectural design so that our model works with the current world trend. To integrate smart meters into the SG, a recent report has been published that discusses smart meter innovations and benefits with the results of The Institute for Electric Innovation's (IEI) 2015 Smart Meter Survey [102]. It shows how smart meters are important for the SG. Energy providers installed 65 million smart meters across 50% of US households. It could reach up to 70 million smart meters by the end of 2016 and 90 million by 2020. It is leveraging smart meters to monitor electricity consumption better. Energy providers are investing $32 billion in the SG in 2016.

2.6.2 Discussion of security and interoperability challenges

There is a problem of smart meter physical security which is very difficult to guarantee. However, most governments are deploying smart meters to Energy users, which is significant. Our design relies on this. Some malicious activities may be found to operate smart meters, which needs to be minimised, for example, distributed denial of service attacks (DDoS) on smart meters. There is a paper [103] which modelled all the malicious activities against the smart meter by using the Gaussian process to generate an early warning system against the malicious attacks. In the advanced metering infrastructure, specifications may reduce that risk according to the OpenMeter project [104].

The use of TCP/IP, interoperability and affordability can be considered to be the key challenges in the transformation of the SG. Although there are some challenges, it will not be impossible to introduce IoT to enable smart meters in the SG infrastructure. However, the OpenMeter project suggests [84] using the proven standard IT systems without reinventing the security issues. It is important that open standards are crucial to update the security of the Commercial Off the Shelf (COTS) hardware and software. Otherwise, it is likely to be deployed widely in the Smart Grid infrastructure. However, the IoT would be more secure in future technology. Security risks exist in network technology architecture. It will not be possible to secure fully. New technology arrives on the market regularly; black hat hackers may breach the security for their personal gain and make the technology vulnerable. Industry best practices and the proven universal standard is necessary for devices that could be used for the SG.

The vast market potential of the SG revolves around the deployment of universal devices so that it holds the open standard to minimise risks and mitigate insecurity. The number of stakeholders in the SG is increasing day by day. Manufacturers, suppliers, regulatory authorities and others must work together to ensure the security of the future grid. Even, electricity users may supply electricity to the market. Therefore, it is important to provide high network-based services that can ensure the integrity and security of the grid. Every aspect of the multidisciplinary consortia may assist the whole complex electricity system by sharing their skills and competencies. Successful co-operation among academia, research centres, manufacturers and IT companies is important in order to address the challenges of the grid. Most countries have invested in transforming outdated grid technologies. They are facing the challenge of new integration of the system through technology.

Another aspect of security is also important to data security. Concentrating on the protection, security and interoperability of data is a dire need for the future grid. An open and secure ICT infrastructure is key to the success of the SG. Robust data privacy and security in the ICT infrastructure systems would reduce the cost of the grid, and that needs to be addressed. However, this thesis is not concentrating on the data communication aspect of ICT systems. It would be beyond the scope of the thesis. Although it is an important aspect of the SG as a vigorous ICT system benefits energy consumers with respect to transparent billing information, the reduction of outages, above all, it brings an ultimate saving for them.

Policy and legislation should also support all these developments of the grid. Regulatory bodies are responsible for ensuring reliability and evaluating the risk of investing in SG technologies. It should not be a case of taking the cost of the transitional grid from consumers' pockets. Electricity users would be able to reap the benefits of real-time dynamic pricing if all these regulatory policies and strategies assist in regulating distribution, generation and dynamic pricing systems. Consequently, the future SG depends on robust communication and regulatory coordination, too. The cybersecurity issue is also a vital aspect to consider for smart metering technology. Some of the groups like vengeful persons or extortionists may collect data from the systems.

To make the electricity grid more intelligent by 2035, the Smart Grids Strategic Research Agenda (SRA) "Smart Grids (SG) SRA 2035" [74] is actively undertaking long-term research. They are addressing the CO_2 emission reduction of at least 80% by 2050. EU energy production will have to be almost carbon-free. However, these activities should start now for the calm transition from the traditional grid to an SG through the European Electricity Grid Initiative (EEGI) by 2020. It would achieve flexibility in demand and response by 2035. It focuses mostly on technology-related research [74]. They try to ensure optimisation of the cost and environmental performance in the light of penetration of renewable energy generation.

SG operation was an issue towards accommodating overall ambitious climate policy. The Danish government commissioned a climate change policy to phase out fossil fuels by 2050 [105],[106]. This is an ongoing policy set-up. They are on track to deliver their goal. In order to resolve the problem, the Danish Commission on Climate Change Policy, 2010, set high policy milestones that show that they want to fulfil the great proportion of their energy needs by renewable energy, in particular by wind, by 2050. Their expansion of offshore wind turbines would be one of the great sources of renewable energy: there is a requirement of between 10,000 MW and 18,500 MW wind power in 2050. Our model can contribute to it because a DR solution would help to achieve the goal by 2050.

There is a debate on “Essential for the transformation of the European energy system, deserving more attention and transparency” in Europe [107], how communication will be established between the energy providers and users, who will access real-time customer data; and how interaction may take place between them. When energy users start producing electricity and shift their load to maximise their own economic benefit, then the public grid needs flexibility for a whole, stable energy grid. All these debates take place not only in Europe but also across the whole world. The Smart Grid would be the answer; our proposed model contributes the solution to the part of the debate.

2.6.3 Discussion on energy scheduling and incentive-based challenges

Decision support tools for residential customers to optimise energy services [7] have been claimed as developed. Scheduling the distributed energy resources can maximise the benefits by using Particle Swarm Optimisation (PSO). They are following traditional methods of coordinating the scheduling problem based on existing electricity tariffs. Our model is not suggesting the traditional prices, rather it is suggesting real-time pricing avoiding the complexity of scheduling problems.

Incentive-based energy consumption scheduling algorithms [108] have been developed by considering DR problems. These share the different levels of information in the SG and introduce an incentive for consumers to achieve an aggregate load profile suitable for them. It depends on how much information consumers share in order to achieve an ideal flat profile for the consumers. They used a distributed cooperative algorithm game to reduce the cost.

Our model does not consider incentive-based rather price-based DR. In addition, the model is not dependent on consumers' information sharing. Moreover, it is not clear what type of information they expect to optimise their algorithm with. In [65], the authors consider ECS in the case of convex functions using a game theoretical approach. They assume that daily load is proportional to the daily cost of the energy network with constant independent load scheduling with a hypothesis that implies utility costs are linearly bounded in any situation. Our model approach is stochastic and does not consider scheduling devices.

One of the models [59] assists a retail EP to offer day-ahead hourly prices to maximise the electricity providers' profit. It implicitly assumes that electricity users need to respond to posted prices in the distributed network. There is no indication of user benefits based on their preferences. An energy consumer's willingness is modelled [109] probabilistically and estimated based upon the user reaction to the prices. Hence, they can adjust an offered price based on their behaviour. This allows energy suppliers to declare the prices for the Energy users from aggregate demand by considering scheduling flexibility. Our model will not take behaviour on price into account; rather it considers their comfort, modelling their reduced bill compared to the traditional bill. Our model concentrates on overall load from a user perspective as well as energy providers' peak load perspective instead of scheduling flexibility. The paper [110] proposed consumption state definition with virtual experiences in the Q-learning algorithm addressing the backlog rate. We have proposed algorithms which do not consider the backlog rate; rather they address the users' bill minimisation whatever load, based on stochastic approximation.

A forecasting mechanism was studied [111] and some of the mechanism compared the different techniques used for Willis and Northcote compared 14 forecasting techniques. However, forecasting load from the historical load would be an idea to predict the current load, but a stochastic process allocates the instant price based on user load, and this forms part of our model.

2.6.4 Discussion of scheduling problems

In load scheduling, the paper [112] used Intelligent Decision Support Systems (IDSS) to receive a consumer's response. They developed a heuristic-based cost model based on TOU, RTP and 2 Tier Pricing (2TP). The algorithm schedules controllable appliances. Again, we argue that a stochastic process is better than a heuristic approach as the stochastic process can handle loss functions and the nature of the data would be probabilistic in nature. Our model minimises the load from the user side in considering the overall peak load. Our methods are different from the work presented in that paper. The paper is also a comparison of scheduling algorithm problems. Potentially, our model is not looking into schedules, rather it concentrates on reducing the overall price, which is helpful for the users.

Some demand management have been studied with the technique of Mixed-Integer Linear Programming (MILP) [113], Direct Load Control (DLC) [114] and branch bound [115] are presented in users' load scheduling problem. Metaheuristic approaches are also proposed over the past two decades like Particle Swarm Optimisation (PSO) [116], and natural phenomena influence Ant Colony Optimisation (ACO) [117], Simulated Annealing (SA) [118] and Genetic Algorithm (GA) [119]. Our demand management programme is designed with the stochastic based Simultaneous Perturbation Stochastic Approximation (SPSA).

In the Smart Grid, a heuristic approach may not be suitable because of the stochastic nature of the data. The heuristic algorithm may be useful for the embedded system such as a decision support system. Usually, a heuristic approach picks up some combinations of input data but not randomly and with no guarantee to find the correct optimal solution. However, it depends on the scenarios: it may be much slower than a stochastic approach. However, stochastic approximation uses the random approach from a whole range of possibilities to reach the optimal solution, and implementation is much faster than a heuristic approach. Randomness can be of two types, one is Monte Carlo algorithm like MCMC, simulated annealing, and Miller-Rabin primality testing which finishes in restricted time but with no guarantee of an optimal solution; but another type is Las Vegas algorithms which do not follow restricted time, rather find the optimal solution.

However, we have taken a stochastic-based approach which can also handle non-differentiable function and reach an optimal solution. There is a huge discussion on different optimisation techniques; comparing those techniques would be another dimension of the thesis like reinventing the wheel in statistics. We have used techniques which are useful to achieve our proven RTPS model.

An intelligent Home Energy Management (HEM) algorithm [117] has been presented for household loads with a priority, price update interval presented [118] with the requirement of power load deviation from the expected load, and it is highly competitive regarding achieving a cost for the power load. The Heuristic Aggregator-Based Resource Allocation [114] has been presented as a demand response approach for residential consumers and proposed profit of the aggregator. The authors admitted that the lowest possible price might not be possible due to a set of constraints [107]; it is not regular re-optimisation with an updated state. In a nutshell, a heuristic approach may not handle the probabilistic nature of the data, and our model addresses that issue so that it handles the probabilistic nature of the data.

A paper integrated automation for optimal demand management in commercial buildings considering occupant comfort [120] and presented that it mitigates the peak electricity demand charges for any building. The paper addressed energy management in commercial buildings. It adjusted the temperature with environmental preferences. It concentrates on the individual plug-load level and building performance, and it essentially concentrates on the building rather than energy load reduction, not by analysing the users' loads. Our model concentrates the SG overall peak load reduction which saves the energy providers' costs.

Some of the literature focuses on long-term carbon emission impact analysed in the DR model. An economic forecast using a general equilibrium model has been presented by considering multiple scenarios. It suggested DR has little impact on carbon emission from electric power generation [121]. It can be considered as an alternative to low-cost peak-hour load balancing without increasing carbon emissions. It addresses the environmental issues like carbon emissions; this DR model would not address users' pricing issues.

Cost savings in smart homes would be a motivation [122] for the user perspective. The study shows optimisation methods are applied in the literature. The survey shows trading energy to neighbours is another way of cost minimisation. It claims that forecasting prices can optimise energy cost in advance and the work developed unified cost optimisation frameworks. A smart home could be an application which would able to provide automated services. It brings better energy management into dwellings to ensure comfort. Residential energy consumers may be prosumers, which means they can produce and sell energy to others as well as consuming it. A set box (STB) [123] gateway has been proposed between the energy grid and a smart meter as well as appliances. The STB displays pricing through a home area network. It does not consider intelligent scheduling; it has to do the scheduling on a manual basis.

2.6.5 Discussions on energy management systems aggregators

The survey shows that Energy user involvement is a principal element in the DR model of the SG. It is important to improve the efficiency of energy infrastructure, too [124]. Users' disappointment may bring some complexity into the system. Users' involvement at the time of ancillary services in the DR may enhance systems regarding robust management. That symbolises the possibility of controlling the load profile, particularly system aggregators on both sides of the system, like in the industry and research arenas.

A review of the recent literature with the perspective of energy management systems has been explored in light of the DR model in the SG. It recognises the challenges and opportunities of the creation of aggregators. Actually, electricity has been operating across a vertically integrated energy industry system chain, particularly generation transmission. That works as the Ancillary Services (AS) which works with deregulation and liberalisation and becomes an independent entity. That creates additional difficulties in the procurement of the ancillary services. That is one of the reasons electricity markets may lead to a complex structure.

2.6.6 Discussion on IoT devices constraints

The Internet of Things (IoT) [125] is an embedded system which can identify connection easily even within the existing internet structure. This may offer an advanced connection for any system; it can cover beyond machine-to-machine communications. It covers a variety of domains and protocols. These kinds of interconnections can lead to the automation of the SG. Our Price Suggestion Unit can be integrated with IoT devices and may work smartly. The new application development would follow the Machine-to-Machine (M2M) networks approach [126].

There are several constraints that may arise for M2M such as bandwidth, storage and computation. It may introduce some challenges such as the shortage of spectrum problem, and a huge number of devices [127] to design the M2M. Most of the research concentrates on resource management, sensing, congestion control and security.

2.6.7 Discussion on dealing with unstable malicious users and energy providers

The paper [128] dealt with Unstable Energy Providers and Malicious Users and modelled their behaviour. Energy providers manage a Power Market Scheduling Centre (PMSC) which broadcasts their pre-set prices to users. They proposed the Mechanism of Identification and Processing (MIP) to identify malicious users and providers. They used a heuristic algorithm called the dynamic pricing algorithm with Malicious Users and Unstable Energy Providers (DPAMU). Our model addresses this issue already, as the stochastic simultaneous perturbation method is able to handle the all loss function which is moulded from malicious users and providers.

2.6.8 Discussion on web interface issue

The Energy Aware [129] system developed for the Smart Home integrates energy features. It uses the Open Services Gateway initiative (OSGi) [130] Alliance framework. It is built on top of Hydra which is a middleware structure to expedite the smart communication with heterogeneous devices through a Peer-to-Peer (P2P) network. It can monitor the data that are received through the devices. Web interface developer can integrate various types of devices to an application regardless of communication technology such as RFID, ZigBee, RF, WiFi, and Ethernet and so on by using Hydra. It is really an adaptable technology. It claims that a smart home system allows the data to be presented in a meaningful context to interact with the environment. It argues that energy user interfaces can show the information regarding the price and usages. Our model has contributed a price suggestion unit. Arguably, it is taking a balanced approach as it is maintaining both SG and Smart Home perspectives. The energy information gateway system then improved it by integrating smartphones. Our argument is that once our system is in operation it can be controlled by any smart device like a phone. The Plogg sensors are integrated with the Hydra framework [131] using the Plogg Software Development Kit (SDK) with the Java interface (JNI). OSGi with Simple Object Access Protocol (SOAP) communicates with the Hydra devices and collects information. This system used the UbSLense architecture to display information.

Awareness in the SG has increased [132] through monitoring systems based on the RESTful architecture. The system used Plogg smart plugs to collect the users' data by Bluetooth. The gateway would be a web server and users can obtain services from that gateway. Web interface and mobile interface show real-time consumptions. Users can interact with the interfaces. The gateway communicates with the Ploggs sensors every 30 seconds. It is just for developing energy consumption awareness so that users do not waste their energy. Our model interface would be real-time interaction with users who would respond to the system's suggestions.

2.6.9 Optimisation technique in our model

In the electricity infrastructure, various techniques have been used to improve energy efficiency. When a system is stressful, Demand Response (DR) is being considered as a very effective and reliable solution [29] in the SG. Electricity price-based DR can be considered. Systems constraints and computational complexity are the key issues in the optimisation procedure. Intelligent and autonomous controllers and advanced software are being used as new technologies in the SG. Two-way communications between EP and energy users are important to develop a distributed advanced energy delivery network. Technologies are employed for the entire system to improve efficiency, reliability and safety of the system [133]. Transition to energy efficiency is a key concept of the SG, where volatile demands and renewable energy are concerned with the scalable information processing architecture [134]. DR is a subset of Demand Side Management (DSM) that manages customers' demand and supply based on their time shape. DSM can yield significant savings [135] in both energy generation and transmission. Elimination of blackouts reducing operational cost and CO_2 emissions reductions are the key advantages of DSM [136].

As this is multivariate analysis, it is not possible to fully analyse and understand some of the stochastic algorithms without advanced mathematics. Modelling endeavours to find an optimum objective price function that would benefit clients and EP as well as the welfare of a society. To gain the outcome of the function, we have used the Simultaneous Perturbation Stochastic Approximation (SPSA) optimisation technique

[137]. Search and optimisation techniques would provide the approach to taking the best decisions in the problem: finding out vector P that minimizes a scalar value loss function by solving the equations.

This method is useful in case of direct measurement failure of gradient function g (P) with the diverse values of P. For a multivariate system, SPSA is useful. It also works in stochastic gradient or gradient-free scenarios. To gain precision, it assists to reduce loss dimension during the process. This SPSA works better in the stochastic environment with the availability of loss measurement, and it is based on for example Y(P) =L(P) + E at various values of P, where E is a noise function.

In particular, in relation to the loss function weights, SPSA exposes this property. For large sample productivity, asymptotic normality of SPSA helps to produce an accurate conclusion. SPSA has been successfully applied to many optimisation problems such as industrial quality improvement, pattern recognition, queuing systems, air traffic management and military planning, aircraft design, bioprocess control, chemical process control, fault detection, human-machine interaction, sensor placement and configuration, and vehicle traffic management and so on.

To reduce the number of measurements in high-dimensional problems, SPSA is especially efficient at providing a good solution. We used the convex convergence technique where the general norms of the convergence function which is three times differentiable, but Ying et al. [138] omitted the differentiability requirement and developed convergence by using convex analysis. Gradient approximation in SPSA would be achieved by perturbing the elements one at a time. Accumulation of loss measurement Y(P) at each of the perturbations, all elements are randomly perturbed together to obtain two loss measurements of Y(P) for two-sided simultaneous perturbation gradient approximation. The mean-zero P dimensional random perturbation vector has a user-specified satisfying distribution conditions and c_i >0 is a positive scalar. The numerator is the same in all P components of $g^i(P)$. The number of loss measurements needed to estimate the gradient in SPSA are two, regardless of the dimension of P. Moreover, comparing the efficiency for Finite-Difference Stochastic Approximation (FDSA), SPSA is very significant, and SPSA is rightly chosen because FDSA is 412 times costlier than SPSA for the termination of the algorithm.

2.6.10 How optimisation problem used in the real world

Some of the research used a mathematical optimisation technique [139] based on the gradient method contrary to that currently used by some other researchers based on non-gradient methods like genetic, simulated annealing or PSO; these search methods might sometimes be not viable. In the real world scenario, how the optimisation techniques are working shows in figure 9 (Appendices). It shows the real world practical problem identified, defining the problem is a challenge then move on a solution, if the solution is effective and efficient then take the solution otherwise it will be cycling to find the solution. Problem formulation is the problem, well-defined problem is the problem half solved. We define our problem and find the solution in the model by this procedure (figure 9, Appendices).

2.6.11 Discussion on others' algorithms, compared to the proposed one

The optimisation is an issue of determining the optimised prices; Vardakas et al. [29] explained that it has two aspects, either deterministic or stochastic, and variables can be designed with vector and integers. Moreover, the optimisation does not mean optimum values can be achieved: there are so many uncertainties involved, and computation might be complex. Classical optimisation procedures suppose linear or quadratic programming are applied; if complexity arises then heuristic approaches can be used, if the total solution is based on uncertainty then the stochastic process can be applied.

A linear sequential optimisation process has been applied, and this algorithm schedules Thermostatically Controlled Appliances (TCA) based on price and consumption forecasts. Some of the optimisation processes consider task-scheduling and energy management appliances. Heuristic-based evolutionary, Binary Particle Swarm Optimisation (BPSO) heuristic algorithm, Particle Swarm Optimisation (PSO) and greedy search algorithm Lyapunov optimisation, all cannot handle uncertainty. In that case, the stochastic approach can manage uncertainty. Markov Decision Problem (MDC), Q-learning algorithm with some other methods such as Branch and Bound method, Signalled PSO (SPSO), Benders Decomposing algorithms and Pareto-based optimisation methods are used at different times to deal with certain problems but not uncertainty.

To defer loads and attempt to follow desired demand, it has been proposed [48] that heuristic optimisation is optimised to avoid overly-homogeneous optimised consumption patterns with significant peaks [140], which also proposes an additional safety mechanism. Price-based incentives are implemented in day-ahead planning in [48] and [140], and two-way communications are required between utility and users as at every time step there is an exchange of information about the day ahead. Fuller et al. [141] proposed a double-auction market technique that requires the exchange of load or price data pairs.

There is a high computational complexity of the centralized optimisation process involved in combining Demand Response and distributed generators, and it is perplexing. For dynamic Demand Response, varying time price, the energy cost of the customers' bill reduction and management of the storage of surplus wind, solar energy and distributing energy in peak time, the stochastic methods play a vital role. To address future demand, Power Distribution and Planning [142] addressed the size of future substations, and better location with a viable economic solution though user privacy is concerned [143].

The Stackelberg game approach [144] tries to maximize the social welfare of users. The EP controls the users who follow only their instructions. Users do not need to submit their requirements when they start receiving energy from their providers, but detailed energy consumptions are to be incorporated in their algorithm. The automated fashion of smart RTP pricing in the Demand Response approach can influence customers individually [145] and voluntarily reduce their loads by use of pricing signals.

Considering all of the optimisation techniques for RTP Demand Response modelling, a stochastic optimisation technique would be better to handle all of the loss functions like malicious users' responses. Whatever the situation of users or EP sides, the probabilistic nature of the data can be handled properly by a stochastic process [63].

A stochastic process is being proved in many fields like in traffic systems with queuing theory and many areas of mechanical engineering. It has been useful in queuing, and stochastic processes calculate congestion in different data networks, particularly, in noisy environments, modulation and detection of signals. It is the process of calculation of random probabilistic data, even not only in the loss incurred situation but also in a noisy environment.

As the grid is a huge environment regarding data communication, calculating prices would be complex and stochastic [146] is the solution for it. Stochastic [42] is useful and effective in SG technology, especially in Demand Response programmes. It is applicable to so many disciplines including engineering, operations research, physics, biology, economics, finance and statistics.

2.6.12 Discussions on different models

Many methods have been used for price prediction, like linear programming or convex methods studied in the domain. The paper [67] proposed mixed methods for appliances. It is modelled as power consumption and delay functions. The delay cost depends on consumers' preferences. It considers total consumption of all home appliances on an hourly basis time slot. It considers the IBR-based price: if the price exceeds a threshold level the price would be increased, if not then the lower amount would be charged. It simulates the result with interruptible and non-interruptible appliances that would be scheduled. It uses a scheduling technique. Our model does not consider a scheduling technique rather consider RT price.

There is a demand-side model discussed in [48] for deferrable devices which are highly time-insensitive. Some of the models are based on load shifting or scheduling-based. Some of them used heuristic approaches with an Evolutionary Algorithm (EA) that would solve the minimisation problem. A pricing model is discussed in [37] for the default customer behavioural effect on DR. Non-linear responses are analysed with the mathematical functions like exponential, hyperbolic, linear, logarithmic and potential. Results are compared with users' load functions. The paper [39] experimented on CPP involving 123 customers by using non-parametric mean estimation. They had two groups where the treatment group consumed 12% less than the control group during the experiment. They used incentive-based DR but our model is on price based DR.

Dynamic pricing programmes [54] could reshape the relationship between energy users and EP. The paper analysed peak load reduction, bill impact and user satisfaction, and reviewed the various factors that have an impact on scalability. The pricing model [59] with a smart meter and DR shows that some factors support the RTP like a smart meter, regulator interest in the DR programme and an organised electricity market. This Day-Ahead Real-Time Pricing (DA-RTP) model offers the optimal price assisted only by the retail provider by using Non-Linear Programming (NLP). It discusses RTP implementation which may be affected because of some technical issues such as the lack of smart metering, and communication and control systems. The paper [61] proposed a pricing algorithm with scheduling device ECS.

We are not considering scheduling devices. We have discussed more this paper at the end of the chapter.

The paper [69] discussed the DR model on the instability of power grids while RTP runs. It discussed the clearing prices of wholesale electricity. RTP generates the loop between market and physical layer. It defined the price instability between the producer and the users' ratio of price elasticity. The paper [72] illustrated load management strategy by using two case studies. It assumes that it allows energy usage control. It used heuristic optimisation techniques. The Quasi-Dynamic Pricing Model [73] was presented to minimise bills by using TOU. It assumes that energy cost depends on interruptible and non-interruptible jobs. It used base price and penalty term. Our model assimilated RT price quite differently.

Existing DR programmes generate inefficient price information [75] that can be solved by demand subscription. Considering subscribers [86] who share common energy sources, they would be equipped with an Energy Consumption Controller (ECC). This model used microeconomics to maximise the utility for optimal price. The paper [91] suggested a bi-level programming approach by using Karush–Kuhn–Tucker (KKT). It replaces the lower level problem and multiple programming into a single one. Residential deferrable, non-deferrable and interruptible appliances were used for the model [92] which applied stochastic optimisation via Monte Carlo (MC) simulation. It used scheduling techniques. The paper [108] proposed a dynamic price with incentive-based DR mechanism with the optimal scheduling algorithm under NP-hard. Our methods are quite different from this paper as we have proposed price-based DR.

Considering the energy subscribers who communicate with the Energy Providers managed by Power Market Scheduling Centre (PMSC), [128] found some malicious users. It addressed the malicious users' identification and processing and proposed a dynamic pricing algorithm with Malicious Users and Unstable Energy Providers (DPAMU). An autonomous software agent was introduced in the paper to optimise the electricity usages. It assumes the Decentralised Demand Side Management (DDSM) model [140]. By using average UK consumption profiles for 26 million homes, the agent can reduce peak demand as well as carbon emissions.

To address the DR scheduling problem, the paper suggested the Stackelberg game approach. It derives Stackelberg Equilibrium (SE) between the Energy users and its price. It assumes that this model [144] can control load uncertainty. The paper [143] proposed DR with electricity privacy protection by using an online stochastic process. It used the Monte Carlo (MC) simulation. The research [147] solved two-stage optimisation problems like the quality of usages with bill and profit of the retailer. It uses the Simulated-Annealing-based Price Control (SAPC) algorithm to solve the non-convex price optimisation problem.

Considering the above researchers, some of them use scheduling techniques. Our model considers current electricity consumption in a time slot wise format with overall appliances. It also addresses user preferences with a stochastic approximation. We named our model the **Real-Time Price Suggestion (RTPS) model**. We have a novel Price Suggestion Unit (PSU) to address the energy bill and Peak-to-Average Ratio (PAR). The above researchers used the stochastic method with scheduling technique. Our model is modified and a different technique assimilated. There is an algorithm [61] proposed that estimates future demand to minimize the electricity payment of users without considering their responsiveness. Partially involving users to shift the load helps to reduce PAR. They have used appliances and simulated with the simulation unit. It uses schedule-based appliances which are not fit for the current scenario. They did not consider the customers' preferences. To implement the model, every user must have scheduling smart devices to communicate their ECS, which may not be possible for the current scenario in the world. We use the current state of real data in different buildings that are obtained from different appliances in our model. Our proposed novel RTPS model answered all of the hypothetical questions.

2.7 Thesis contribution in a tabular form

Descriptions							Key areas where this thesis has made a novel contribution.				
Reference	Year	Critical Analysis	Method	Program	data	Algorithm	Utilised Stochastic Optimisation	Incorporated customer Response	Model contributes social Welfare	The model includes price Suggestion	Model developed PSU
This thesis	2018	This thesis address probabilistic behavioural data, users' savings, social welfare and Energy provider's savings by developing novel price suggestion unit through the stochastic approximation in the smart grid	RTP	DR	Half hourly	Simultaneous Perturbation Stochastic Approximation (SPSA)	Yes	Yes	Yes	Yes	Yes
O Chris[112]	2016	General pricing model, Reducing Peak load	RTP	DSM	Scheduling	NP-hard, Heuristic	No	No	No	No	No
Q Tang [148]	2016	malicious users for the unstable energy provider	N/A	N/A	market Scheduling	Heuristic	No	No	No	No	No
A Amjad [6]	2015	weather condition, save user side cost	N/A	DR	Wind turbine	MINLP	No	No	No	No	No
B. Kim [110]	2014	Energy consumption-based approximate state definition.	N/A	N/A	No	Reinforcement learning	No	No	No	No	No
P. Samadi [61]	2014	Minimize the peak-to-average ratio (PAR)	RTP	DR	Scheduling data	Finite Difference and Stochastic Approximation	No	No	No	No	No
P.-Y. Kong [118]	2013	Communication based paper. determine price update step size	N/A	N/A	N/A	Heuristic	No	No	No	No	No
Z. Chen [143]	2013	Energy privacy protection	TOU	DR	Scheduling	Monte-Carlo	No	No	No	No	No
F. Meng [91]	2013	Electricity retailer determines the real-time retail prices	RTP	DR	Scheduling	bi-level prog. model, branch and bound	No	No	No	No	No
L. P. Qian [147]	2013	Reduces PAR	RTP	DR	Scheduling	Simulated Annealing	No	No	No	No	No
J.Lujan [72]	2012	User side bill reduction for Electric Vehicle	RTP	DR	Hourly	Heuristic	No	No	No	No	No
M. Doostizadeh [59]	2012	maximize the electricity provider's profit	RTP	DSM	Hourly	Heuristic	No	No	No	No	No
Z. Chen,[92]	2012	Minimizing electricity payment	RTP	DR	scheduling	MILP /Robust optimisation	No	No	No	No	No
M. Roozbehani, [69]	2012	Addressing system volatility	IBR	DR	Whole sale	autoregressive prediction models	No	No	No	No	No
C. Joe-Wong [109]	2012	Reduce the cost incurred by the provider	TOU	DR	Scheduling	dynamic programming approach	No	No	No	No	No
S. Hatami [73]	2010	Minimising bill	RTP	DR	Hourly	Quasi-Dynamic	No	No	No	No	No
H. Chao [75]	2010	Contract-based baseline through demand subscription	TOU	DSM	Hourly	Heuristic	No	No	No	No	No
A. H [67]	2010	Reduce PAR in load demand	RTP	DR	Hourly	Heuristic	No	No	No	No	No

2.8 Key issues to be addressed

So far, a variety of research has been undertaken related to Smart Grids, but these are lacking in addressing issues such as customer responsiveness and price optimisation for end users and energy providers. The research undertaken as part of this work has addressed these key issues and developed an optimised algorithm through which users can express their choice, energy providers can reduce their energy aggregate load, and users can reduce their bills and get this as a mobile app.

2.9 Aim and objectives of the research

2.9.1 Aim

This research aims to develop a real-time optimised Demand Response pricing model through a price suggestion unit to accommodate users' choice without interrupting their energy preferences.

2.9.2 Objectives

- Reducing consumers' bills by their consumption that assists the EP to take a decision about real-time prices.
- Reducing Peak-to-Average Ratio (PAR) energy load so that EP and users both can achieve mutual benefit.
- Reducing expensive power generation while meeting the peak demands addressing the pollution obligation that should be met by the energy provider.
- To maximize power system reliability, change the demand regarding supply with a high perception of renewable energy, especially solar and wind.
- Reduction of the overloads of the distribution system by using a Demand Side Management system that takes real-time decisions.
- Attract the interest of consumers to participate in Demand Response programmes through the provision of price suggestions without interrupting their preferences.
- Ensure benefits for all categories of customers and accommodate users' desired electricity pricing on their usage.
- Simplify the probabilistic nature of data complexity and provide an optimised price for customers.
- Provide best-optimised value by comparing multiple optimisation techniques.
- Maximising social welfare and maintaining system stability with minimum curtailment.

In order to address all issues, we are going to discuss our methodology in the next Chapter 3 leading to proposed work in Chapter 4. We have discussed result in Chapter 5 and concluded in Chapter 6.

3 Research Methodology

This chapter is about how the research has been conducted scientifically. We have discussed how we have solved the problem systematically and logically through the process. It is also about how information has been obtained and its ethical justification. Our formulation of the problem has been solved through different techniques which are explained in this chapter. Moreover, we would like to illustrate the research approach. This research is a functionalist approach as descriptive mathematical modelling is the key aspect of the research. The simulation-based technique has been used where simulation tools assist to generate a model regarding the objective function.

3.1 Technique used

3.1.1 Simulation as a technique or method

Our research is based on simulation, the logic behind it and the steps needed, so we need to explain some terms and terminology. We are using the simulation technique because it would be very difficult to get access to a real-world scenario to test our model. We have to choose this method because most of the research is simulation-based. It is very difficult to get into the real industry to get real data and work on it. There are many academic types of research which significantly influence the real industry although those are simulation-based.

This research used the simulation-based technique available in MATLAB 2015 (b). This is the tool that has been used for developing the algorithm. This tool is a relatively easy means of building and testing stochastic algorithms, besides this MOSEK is another tool, which can be used for implementing this algorithm. This method is not explicitly tied to any specific computing environment.

Simulation is a technique which imitates the real world. There is clear justification for using simulation in the academic area. This word “simulation” means imitate exactly. We would have interest in a real-world phenomenon as a researcher and design a model which is similar to the target interest. The model would be simpler to achieve the target. We model the real-world scenario between EP and Energy users where demand and supply are involved.

The real world might be somewhat complicated. However, actual beneficiaries get benefit from the model. Another way we can say this is: if the model is dynamic, then the model can be changed according to the real-world needs. A simulation is an exploratory approach where the problem becomes better understood. By modifying, compiling, debugging the code, it could be more easily implemented.

We present the model with a mathematical equation with a conditional statement. Over time, it can be changed in the future; there is no absolute abstraction in it. It can be changed according to real-world needs. We may need to add more variables or some more logic without changing the fundamentals of the model. In the probabilistic behaviour and continuous probability density function, simulation is the way to test the model. The model involved computer programming languages and toolkits in the simulation.

The tool we have used is MATLAB. It stands for Matrix Laboratory. It is a language which performs highly to compute any program. It can easily solve problems like computation and visualization. It can handle mathematical computation, developing an algorithm for analysing data, modelling and simulation. Some of the user interfaces are graphical so that users can easily find their output. It has an array with data elements.

We have building data on a daily basis with 48-time slots which have matrix and vector formulations. We have solved it in MATLAB with the row, column and pages or levels. It is a state of the art matrix. So, our algorithm is implemented with its standards instructional tools and techniques. It is widely recognised in science, in particular, mathematical engineering research.

We have taken this consideration so that our research is widely recognised. We have used different comprehensive toolboxes from MATLAB, in particular, Arduino patches which we used to collect data from different energy usages. It saved data with .m files that solve different classes of problems. It is used in areas such as neural networks, signal processing, fuzzy logic, wavelets, control systems and many others.

It has five different areas which include languages, working environment, graphics, mathematical function library and Application Program Interface (API). Its language is a high-level language with control flow statements, functions and object-oriented programming features. Its working environment facilitates programmers to manage variables, import and export data and debugging. It is also a kind of graphical system which allows users two- or three-dimensional data visualization. It has function libraries which allow complex matrix computation; in this case, our matrix was successfully computed. Its library also allows writing a program in C and FORTRAN that interacts with MATLAB.

There is a reason for using this simulation. We have used a MATLAB simulation for the energy business in order to experiment and explore a real system. Experiment in the real world is impossible and impractical because of cost and time. The simulation model can assist and generate confidence in designing new things which have not been done before. Stochastic simulation modelling allows the energy industry to be more efficient while they are working on a probabilistic behaviour or random basis.

3.1.2 Other tools (Arduino and Raspberry Pi) used

We have used an Arduino Uno and Raspberry Pi, which are useful to build an electronics project. It is an open-source platform. It has a programmable circuit or microcontroller. It is run in its own operating system that is called an IDE (Integrated Development Environment). It connects to a PC and uploads code to the physical board. It does not require any other programmer hardware to load its code. It connects to the PC by using the USB cable. Its IDE is a version of C++.

Another device is the Raspberry Pi which also plugs into the PC monitor with HDMI cable. It acts like a PC. It takes input by using keyboard and mouse. It has the ability to interact with the outside world using the internet. Its operating system is Raspbian, which is a version of Linux. It comes with the Python programming language and IDLE 3, which is the IDE. New users are also assisted in setting up a Raspberry Pi. Simply, it can be unpacked on an SD card and run on a Raspberry Pi.

Various equipment has been used to make the hardware PSU, as follows:

1. Arduino UNO A000066 ATMEGA328 Microcontroller Board-Heartbeat sensor using Arduino
2. ACS712 30A Range Analogue Current Sensor Module ACS712ELC-30A ARDUINO RAS PI
3. Fit Tek 65 PCs assorted length multi-coloured flexible solderless breadboard jumper wires
4. High-Speed HDMI to DVI (0.9M / 3Ft) male-to-male bi-directional adapter cable with gold-plated contacts (black, blue)
5. Arduino-controlled power outlet
6. USB cable for the connection between the PC and Arduino
7. Arduino SD card
8. Light bulbs
9. Breadboard
10. Electric sockets and switches
11. Raspberry Pi
12. Ethernet cable
13. USB hub
14. And some others.

We have assembled an electrical board where we have connected lights, other appliances like a kettle, mobile charger, washing machine, TV and so on with an extension socket. Figure 10 shows the assembled electrical board. We collected data widely from various appliances through this board. This board is connected to real-world appliances and converted consumption through the ACS712 30A Range Analogue Current Sensor and passed data to our algorithm in the PC to calculate price suggestions and optimised prices for Energy Users.

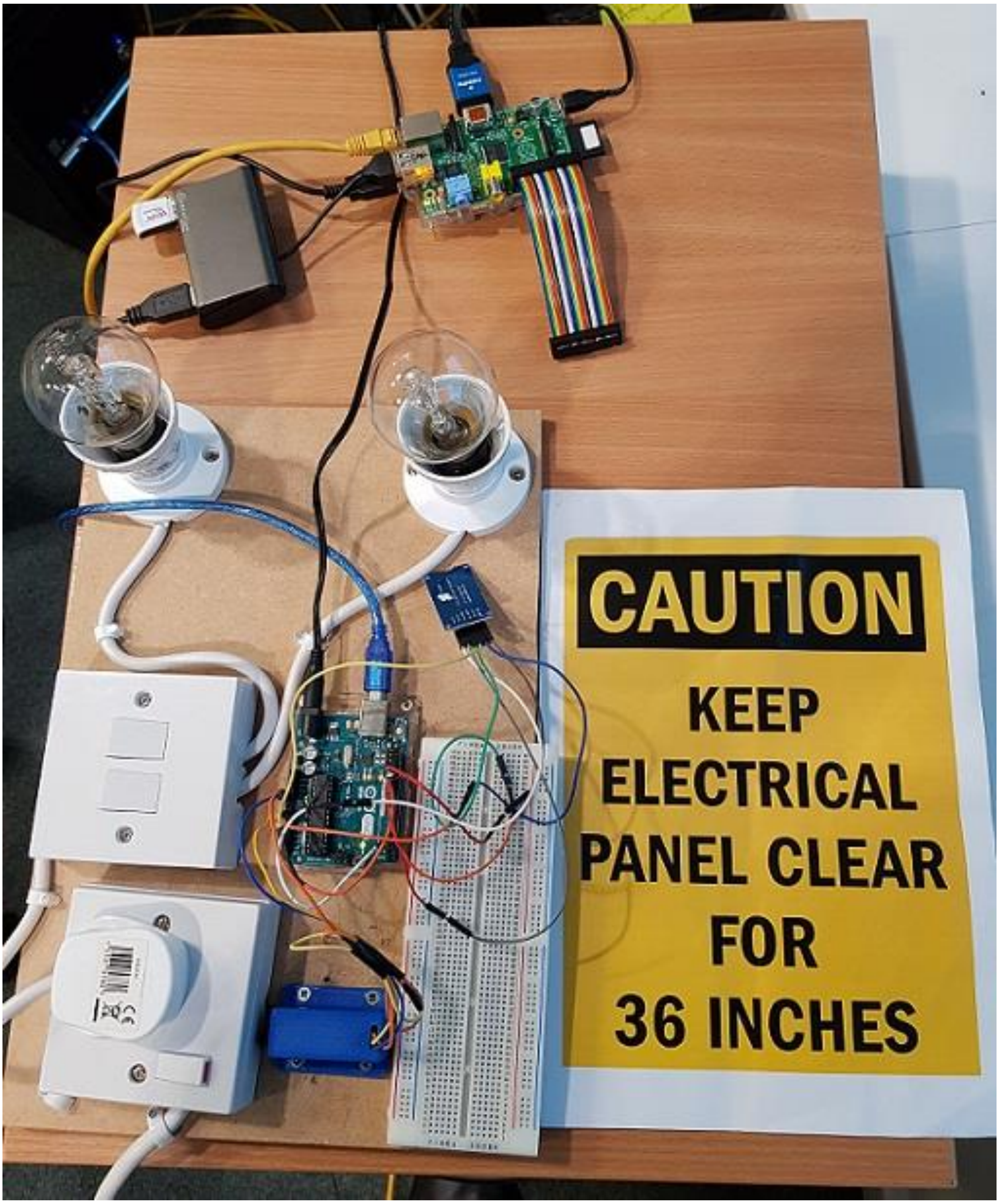


Figure 9: Live energy data that fits in an algorithm with Arduino and Raspberry Pi

3.2 Handling data

3.2.1 Data collection

We collected data from the open sources online based portal of the Department of Education [148] in the UK. We needed domestic appliances and half-hourly basis data, which is difficult to gather, however, we search for different government office data that are accumulated on a half-hourly basis for appliance data in different time slots as we generate the price signal in each of the time slots on a real-time basis. Their half-hourly based consumption in kWh is taken into consideration to generate a price that helps to reduce PAR as a whole.

Besides this, we have collected data from the University of Bedfordshire energy consumption from its portal. It contained ten buildings' data over five years. However, we used one day every half-hour time slot data for the day-based Real-Time each time slot price suggestions. We also have 30 days' data from the five years' data to test how the EP and energy users reduced their monthly cost. It is noted that we have used 14 buildings' day-based data but could not use all 14 buildings for 30 days because of the lack of monthly-based data from the Department for Education (DfE) buildings. So, we analysed day–based data on 14 buildings, but we have used ten buildings for the monthly analysis.

Different companies charge energy prices at different rates; however, they are charging almost similar flat rates, as the UK still had not implemented an SG. For example, one of the EP in the UK is charging a TOU flat rate of 13.844 pence per kWh that is used in our research to compare with our real-time price.

3.2.2 Data processing

The format in which we received data was not good enough to fit in the model. We processed the data in Excel and transformed it into a format to fit in the model in MATLAB. We downloaded data from the DfE portal and processed it according to our requirements. We required the data for four buildings by 48-time slots. We had data for different buildings in different files, so we collected them in one file. Also, we collected data from the University of Bedfordshire, from their portal; we accessed that portal and downloaded with the system cloud provided with a long waiting time because of the huge amount of data. We made 30x10x48 (30 days, 10 buildings and 48-time slots) data for the monthly basis analysis.

3.2.3 Data ethics

These four DfE buildings in the UK show that they have 24-hours energy consumption. We downloaded data from Govt. portal which is available for research purposes. There are no ethical questions about these data as this is open to the public for further research. We have checked with the University of Bedfordshire energy consumption data; there are no ethical issues involved. We applied for a data ethical approval through the University of Bedfordshire ethics committee and received confirmation of approval from them.

3.2.4 Challenge of collecting data

In the beginning, we tried to access real industrial data but could not get hold of them. We searched the internet, and eventually found open source data from the four buildings of the Department for Education (DfE). We contacted the University of Bedfordshire (UoB)'s energy maintenance team, and we received data relating to ten buildings (based upon half-hourly usage, i.e. 48-time slots for a single day). We implemented our experiments using the 14 buildings' data for daily price suggestions, but for a price suggestion on a monthly basis, we used 10 buildings as they have recent and available monthly data.

3.2.5 Difficulties in fitting the data

It is a challenging task to fit experimental data to a model, in particular, it contains many parameters. We faced difficulties in implementing loss functions. However, we did achieve a loss function implementation eventually. This statistical analysis was implemented in many diverse disciplines. Some of the values have been used in several implementations such as the value of the gamma which is 0.101, the value of alpha is 0.602 and these values have been tested with different disciplines [63].

These were used to assess the value of the stochastic process algorithm. We declare the loss function eta which is perturbed in the j^{th} element in the i^{th} iteration. It was challenging to implement, and finally, we manage to implement it. There is a challenge to achieve an optimised value if an algorithm accesses to a huge number of data. We have taken half-hourly data and with its time slot real-time price generation; we ponder that it could be many data points where values have been lost or uncertain; in that regard, a stochastic method loss function assists in recovering the uncertainty.

3.2.6 The computer system used for calculation

The computer system used for generating results is as follows: Windows edition 10 Professional version released in 2015 from Microsoft Corporation. System configuration includes processor: Intel® Core™2 Duo CPU, E8400, 3.00 GHz, 2.99 GHz. Memory RAM 4.00 GB. System type includes a 32-bit operating system, x64-based processors.

Now we are going to discuss our proposed model in the next Chapter 4 followed by Chapter 5 and 6.

4 Proposed Work and Motivation

Considering people's everyday energy necessities, the current traditional grid cannot manage demand and response between the energy users and provider in the grid. There is a need for a demand response programme which can manage the demand and response between energy customers and providers. Usages of energy should be value for money and energy should not be wasted. Researchers address a number of areas in the power grid such as communication technology, security and demand response programme. This thesis focuses on the demand response programme in the grid as the current state of the grid would act as a (bi-directional information flow) Smart Grid. We have discussed various research works in the literature review and placed a proposal for the PhD thesis.

4.1 Key question to be answered

The question forms the key research hypotheses and areas that were explored during this research. The question represents the key aspects that needed to be answered in order to develop a solution that is robust, and that could be applied to real-world scenarios.

> Are users' preferences through Price Suggestion and providers benefit taken into account to produce a real-time optimised price with the consideration of demand response in the Smart Grid?

Most customers are looking to reduce their bills in the easiest possible way. However, there are two types of customer responsiveness found: (I) some are eager to reduce bills and some of them are not; (II) some of them will have priority for comfort not for reducing the price. Nonetheless, every customer should have the right to achieve an optimised price for their consumption.

4.2 Brief rationale

In the energy industry, SG is the topmost priority around the globe. However, because of the immaturity of the implementation, it is complex and difficult to understand. It is sometimes difficult for consumers to grasp the concept of an SG. This modern, efficient grid commits the energy industry in the twenty-first century to connect everyone to efficient, reliable, abundant and affordable electric power anytime and anywhere. In fact, if it is implemented in the UK (for example), it can be connected with other countries of the world, too.

Total energy consumption habits have shown a general increase for almost every type of equipment in our daily life, and this augmented consumption has led to peak demand for electricity increasing at a huge rate. To reduce peak demand, the SG uses a Demand Response (DR) programme. Demand changes follow supply, especially for renewable energy sources such as wind turbines and solar panels that maximize the overall power system's reliability. A distribution management system can reduce overloads and give real-time decisions. The SG can provide mutual benefits for power utility companies and consumers.

We are experiencing more double the population than in the previous hundred years, and our energy consumption is four times bigger than that time. Our energy usages are ten times greater than previous years. We are facing a new, modern world which needs an energy grid with new, modern technology. We need a technological improvement that can assist us to decide the automatic demand response of the energy grid. We proposed a model which integrates DR management.

The proposed model will automatically optimise a consumer's demand and suggest the load shifting for saving money. If someone wants to save more on their bill, they have to respond to the energy providers' price suggestion. The algorithm can handle objective price functions, ignoring the customer's input. However, customers are not required to respond, they will receive an optimised price, but if someone wants an additional reduction from their bill then they can press a button on the Price Suggestion Unit (PSU). This approach will ensure that both types of customers will benefit from the system.

Our model produce an optimised price. It would handle malicious responses of customers; where the system can receive from users missing data or misjudged data, as there is the option of receiving a customer response that will handle both automated input in the system to make the decision. A stochastic process is implied in PCU, which minimises its loss of data and will still provide an efficient optimised price. User input is significant for the energy provider, but some of the users do not respond as they want comfort.

The stochastic approach is considered from customers' demand side on a real-time basis of this proposed model. Details of usage or customer's intentions are used as part of the PSU. The algorithm will address both customers who are very keen on savings and customers careless about saving on their energy bill. In future, it is assumed that every user will be equipped with PSU units along with their smart meter.

This system will address the reliability of the emerging SG paradigm [149],[150] regarding operational aspects, and therefore the Smart Grid's enhanced systems could handle the power system reliability even if it is interrupted. The customer will receive notification of electricity network problems immediately after the problem occurs. Energy users who are equipped with tools would then realise their usage. Then, they can avoid blackouts [151] and optimise their usage by reducing the peak load.

This model considers intelligence and performance, as intelligent performance tools will allow energy providers to undertake their responsibilities to act more effectively and efficiently in the bi-directional and interactive SG. This will help to manage the production of an SG [152] in the operational level of costs. All those efforts would help to implement the 2050 vision [153],[154], and this research will be a partial requirement of that phenomenon.

4.3 Proposed model

This research aimed to develop a real-time optimised Demand Response pricing model, with a focus on the users' demand side of the Smart Energy Grid. This new proposed pricing algorithm would address those issues identified above, particularly addressing users' choice without interrupting their energy preferences by considering a user's price suggestions. Besides this, this model can reduce consumers' bills by their consumption, and that would assist the EP to decide real-time prices.

Moreover, it maximises power system reliability, adapts demand to follow the supply with high penetration of renewable energy, especially solar and wind, as energy providers must address pollution minimisation. It would also ensure the benefits for all categories of customers and accommodate users' desired electricity pricing on their usages, simplify the probabilistic nature of data complexity, maximise social welfare and maintain system stability with minimum curtailment.

This model addresses the energy providers who are eager to minimise the Peak-to-Average Ratio (PAR) regarding the aggregate load demand to provide an optimised price on a real-time basis to customers. Indeed, energy providers are being charged by power generation 'peakers' basis. Furthermore, the 'peakers' mean the high demand period of the electricity over the day. There are terminologies used in the electricity generation. They used basic load that referred to minimum electricity demand over the whole day and peak load means when there is a high energy demand involved. Consequently, EP are keen on reducing Peak-to-Average Ratio (PAR) to reduce their cost. It also addresses the challenge of the uncertain impact on a user profile depending on the energy provider's price selection.

It addresses the integration of multiple energy user sources to produce an optimised price for different types of customers. It is also capable of considering customers' malicious responses to maximise users' welfare. However, automated input from users through the system (and if they missed response of the system, whether that manual input can be accommodated), that is it leads to probabilistic behavioural data. Our model integrated with a stochastic method that handles the probabilistic behavioural data.

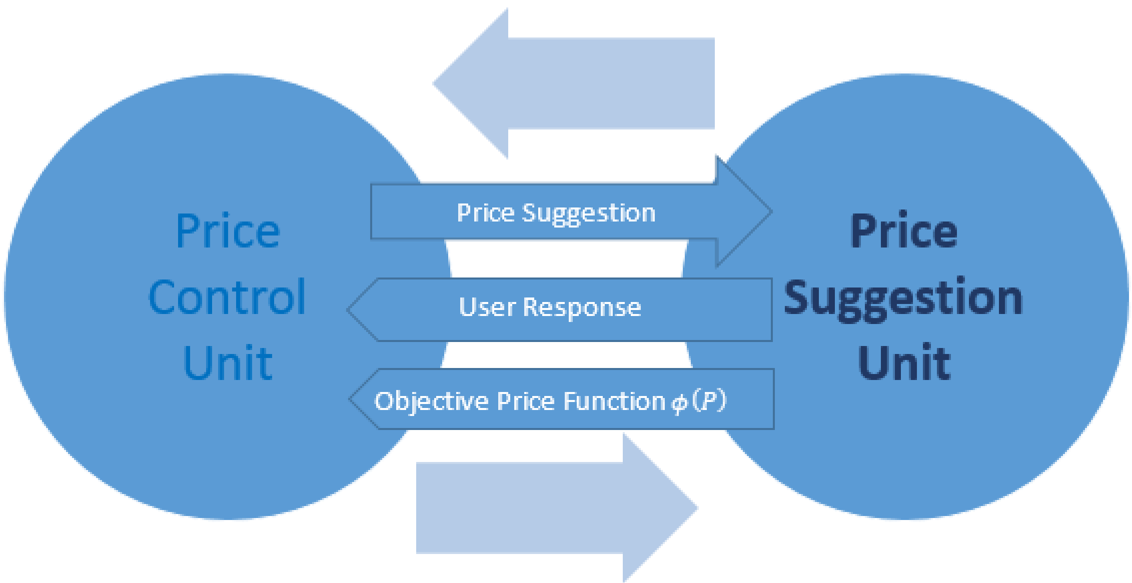


Figure 10: **Proposed block diagram of the pricing model**

A proposed block diagram for the Real-Time Pricing (RTP) model is shown in figure 11, and the algorithm developed for the **Price Suggestion Unit (PSU)** along with Price Control Unit (PCU) is the core contribution of this research. As a whole the contributed model is named the **Real-Time Price Suggestion (RTPS)** model. Implementation of this iterative algorithms of the Price Control Unit (PCU) means that it can minimise the Peak-to-Average Ratio (PAR) of the aggregate load based on information provided by the PSU. In the SG, we assume that users will be equipped with a Price Suggestion Unit (PSU) (newly developed) and the EP will control the price with their price control unit.

4.3.1 How the proposed model will work

The proposed Price Suggestion Unit (PSU) dynamically collects a user's choice based on the price imposed by the energy provider. If users' aspire to reduce their price more, they will respond to the Price Suggestion Unit (PSU), otherwise the Price Control Unit (PCU) will calculate the optimised price value for the customers without counting their responses. Both options are available for consumers because some consumers do not like change as it may be detrimental to their comfort, but other users' do wish to reduce their price value by responding to the PSU. The EP needs the detailed energy consumption data from the users. The EP collects it automatically with the assistance of a smart meter that is connected to PSU. By using an energy pricing algorithm, it would be possible to calculate an optimised price for those customers who are not even interested in the price reduction. However, the user input will assist customers to reduce their energy expenses.

Some users may have a PSU, some of them may not, and some of them may want to make a decision manually. To achieve a better estimate of the likely behaviour of the users, the PSU considers various user responsiveness and different types of objectives of users such as whether the user is seeking comfort and reducing prices. The Price Control Unit (PCU) takes the decision based on the PSU information provided.

Regarding renewable energy pricing, two scenarios can be considered: i) energy providers are distributing energy to users, and there is a price involved, and ii) users can sell their renewable energy to an EP, where there is a price involve as SG is working bi-directional [155].

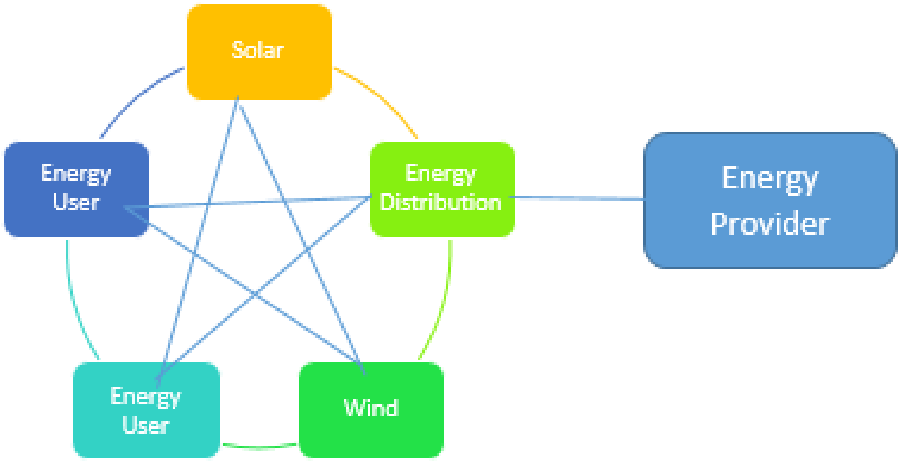


Figure 11: **Mesh network between Energy Provider and Energy User**

Users can communicate with each other, as the underlying communication network is a mesh structure where customers are interconnected with one another. This structure provides significant advantages as they can buy and sell energy with one another. Obviously, an EP is also connected with them. However, there is a disadvantage to it as there are many redundant connections that will incur cost unnecessarily.

Corresponding to that mesh structure, EP to user and user-to-user connections will be established so that surplus energy can be circulated and meet the required demand of users, which is out of the scope for this thesis. To suggest a price for the users based on their behaviour, it would be difficult to assess the fluctuation of their usage, needing machine learning behaviour that may also be a topic of research.

4.4 System architecture design of the model

The main power grid supplies electricity to the end user, but in the middle the energy providers control user energy consumption and prices it. Energy providers pay to the power transmission grid. They place their demand based on their peak load which occurred from energy users' demand. This energy provider is connected to our model in particular by the PCU which connects to the user-side PSU that is connected to the smart meter. We have explained widely in the literature review that most countries are investing in Smart Grid infrastructure. One aspect of their investment is on ensuring placement of a smart meter in every household. A country like the UK has planned that by 2020 that every user needs to install a smart meter in their household. Apparently, the smart meter is connected to all appliances and collects the energy consumption reading. The smart meter can have a bi-directional communication between energy provider and energy users. Figure 13 shows the system architecture design.

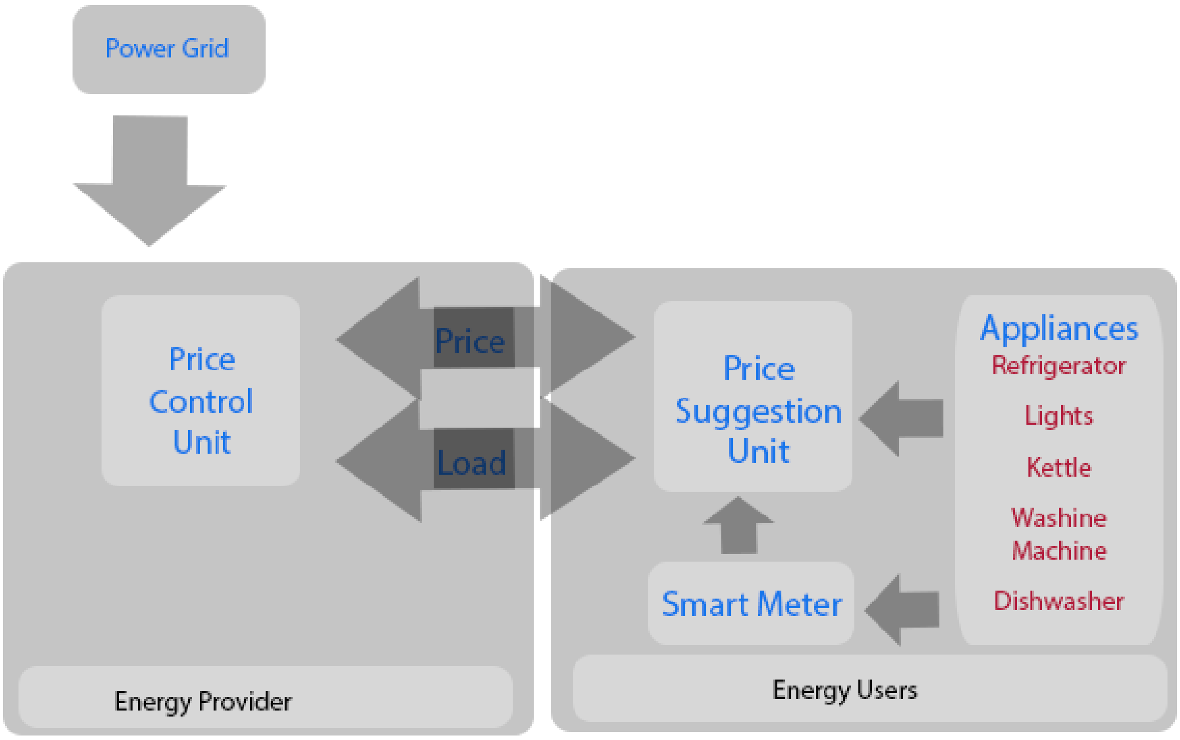


Figure 12: Architectural design of the model

4.4.1 Techniques to be used in the proposed model

An iterative stochastic optimisation technique is used for the Real-Time Pricing (RTP) algorithm for a Price Suggestion Unit (PSU). Real-Time Pricing (RTP) algorithms are useful with the simultaneous perturbation methods [156]. This includes various stochastic optimisation tools and approximation techniques for maximising multiple objective functions such as offering dynamic prices and fair choices for the consumer while ensuring maximum efficiency of the system from the EP's point of view. A stochastic process would be helpful in minimising user prices based on the aggregate load profile in the presence of load uncertainty. There is an optimisation [109] that minimises EP time-dependent prices and provides incentives to users that help to shift their energy consumption. Users' responses allow real-time estimates of user behaviour about prices offered. However, our model is price based DR.

The entire process is stochastic, and stochastic approximation can provide the optimised result. So, the scenario needs to be modelled in real time to ensure the benefit of consumers and the energy providers are maximised [32], [61],[157],[158],[159]. An algorithm called simultaneous perturbation stochastic approximation (SPSA) is based on the simultaneous perturbation technique [137] to approximation the gradient of the objective function which is minimised by changing the element of the price parameter.

4.4.2 System descriptions regarding the current trend of the power grid

Currently, in the power grid, we see substantial half-hourly variation in electricity prices. An EP charges to end users a flat rate TOU or IBR basis. With that rate, Energy users buy electricity during peak hours [147] such as between late afternoon (especially after 6 pm) and bedtime, like up to 9 pm. These significant energy usages during peak time determine the fluctuation between off-peak and peak-time usages. An EP also buys their energy at that particular time with a high cost.

The ideal solution would be for the retail EP to evenly spread demand in different half-hourly slots (energy consumption) utilising demand response management. This research has been undertaken on demand response management by using real-time pricing to reduce the peak to the average ratio by encouraging users to shift their demand to suggested times. The real-time-based energy DR management can determine how much energy is consumed every half hour. Real-time solutions may reduce wholesale prices and gain a retailer profit as well as lower bills for users by responding to time-varying prices.

To achieve the desired level of satisfaction, user preferences are important, and it should be user-friendly for the users so that they can choose their preferences in the SG to reduce their Peak-to-Average Ratio (PAR) load.

Research and solutions so far in this arena have not been addressed in real-time price settings on the EP side, considering the wholesale price by considering user responses. However, implementation of RT pricing would address this issue as the industry is using a huge amount of energy and they would be more interested in user response to price suggestions for their benefit. Energy providers maximise their profit by matching the demand from users on a real-time basis.

In this research, we endeavoured to produce price suggestions for users to reduce their load and ultimately reduce their energy bill. Designing a real-time pricing scheme addresses the problem of how to reduce PAR and for EP maximise profit and minimising the user's energy bill. The challenge is the price announcement from the EP in the price parameter. There are also uncertainties involved with the user responses. However, if we can optimise prices based on responses from users that would assist in reducing the PAR.

For the fixed price for consumption, a user has to adjust their demand by the price. As the SG is bi-directional, the EP can set their price based on real-time demand. Users must be equipped with a smart meter that acts on the real-time scenario. We introduce a Price Suggestion Unit (PSU) where a user finds the suggested price for the upcoming time slot. We would like to optimise in two ways: one is on the EP side, the other on the user's side. Nonetheless, a user does not respond to a suggested price that would not lead to their dissatisfaction. They have some non-flexible appliances which might not be shifted, but they may shift their flexible appliance loads; they obtain an optimised price based on their usage without interrupting satisfaction.

Their bill would be minimised based on their use only. However, they may pay more than those customers who are responding to the suggested price. EP would reshape their real-time price based on user response to maximise their profit. The algorithm will allow each user to shift their usages by utilising an efficient iterative process. A user might interact with the EP by exchanging messages. As the system is bi-directional, that might eliminate some cost uncertainty on the EP's side.

In the Price Control Unit on the side of the EP, the proposed algorithm utilises a Stochastic Perturbation Approximation (SPSA) method to reduce PAR in the system. By considering accurate information from the EP and Energy users real-time prices will be produced. It has been justified that real-time pricing is better than flat-rate pricing. Moreover, user response to price suggestions reduce the PAR. Ultimately, a user is able to reduce their bill, overall peak load will also be reduced, and the EP would be able to reduce their cost to distribute energy. In the end, energy generation and transmission would be less; and the cost is less for less energy generation.

4.5 Designing the Price Control Unit (PCU)

4.5.1 Notations used for algorithm

Symbols	Notation
l_{a_u}	Load per appliance and user
A	Total number of appliances
U	Total number of Energy users
a	One appliance
P	Price vector
t	Individual time slots
T	Total number of time slots
$\mathcal{T}$	All time slots for all users
r_{a_u}	Energy consumptions per slot
p_t	Energy Provider's (EP) price per unit
$l_{a_{u_t}}$	Load per appliance per user per time slot
L_u^t	Total power load
u	One User
min_t	Minimum price charged
max_t	Maximum price Charged
thr_t	Threshold Price based on threshold load
$\phi(P)$	Price objective function to be minimised
$\hat{g}^{\,i}\,(P^i)$	Estimated gradient vector of $\phi(P)$
$L_t\,(P)$	Total aggregate load at time t
σ^i	Step size in i iteration
K	Dimension of vector
c	Coefficient
α	Gain magnitude
γ	Improvement sequence
ε^i	Perturbation vector
I	Iteration enhancement of the algorithm
$g_{max}(t)$	Maximum energy generation
g_t	EP's generation at time t
L_u	Total Schedulable load profile
P_t	Price vector for the maximum, threshold, minimum
P^i	Price parameter in i^{th} iteration
b	Defined building
rc	per half-hourly industrial running cost

4.5.2 Problem formulation in Price Control Unit (PCU)

Let us define a building user based total power load $L_u^t \triangleq \sum_{a \in A} l_{a_{u_t}}$ (1)

and assume that there will be a maximum or minimum charge applied based on the office usages. Let us denote $min_t\ max_t\ thr_t$ as the price parameters, which can be defined as

$$p_t\ (L_u^t) = \begin{cases} min_t, & if\ 0 \le L_u^t \le thr_t \\ max_t, & if\ L_u^t > thr_t \end{cases} \quad (2)$$

Where thr_t is the threshold price parameter that can be selected by the EP that is based on the offices' usual energy consumption, for example the building user consumes 40 kWh in a particular half-hour time slot and p_t the actual price determined by an EP at time t and the total day has been divided into 48 time slots, on a half-hourly basis that is defined as T, where $t \in T$.

To reduce the Peak-to-Average (PAR) of aggregate load, define $P_t \triangleq (min_t\ max_t\ thr_t)$ as a vector of the total set of price vector P = $(\mathrm{P}_1, \ldots\ldots \mathrm{P}_T)$. The price of the electricity depends on total half-hourly basis energy consumption.

Considering the RTP half-hourly basis optimised price value for the clients, we define

$$\underset{\mathrm{P}}{minimise}\ \phi(\mathrm{P})$$

subject to $min_t^{min} \le min_t \le min_t^{max}, \forall t \in T$

$max_t^{min} \le max_t \le max_t^{max}, \forall t \in T$

$thr_t^{min} \le thr_t \le thr_t^{max}, \forall t \in T$

$min_t \le max_t, \forall t \in T$

where $\phi(P)$= max $\{L_1\ (P)\ \ldots\ldots\ldots L_T\ (P)\}$ (3)

There are three elements in the price objective function $\phi\ (P)$. Those are maximum, minimum and threshold prices based on threshold load. The **Pareto-optimality** is the difference between two successive values of the objective function is less than a predetermined threshold. All price parameters are calculated by multiplying the price parameter p_t. If a building user exceeds the limit in that particular time slot, then they will be charged the maximum range of price, otherwise, the minimum range of price would be charged for all their usages.

To measure our objective function, every pricing element change in the vector P, and the jth element of vector P is perturbed. This vector would be measured through the iterative process and the ratio of change of objective function for perturbation of the jth element of gradient vector of $\phi\ (P)$. The price parameter P can be perturbed by this equation

$$\mathrm{P}^{i+1} = \mathrm{P}^{i} - \sigma^{i}\ \hat{\mathrm{g}}^{\,i}\ (\mathrm{P}^{i}) + \epsilon^{i} \tag{4}$$

Where $\hat{\mathrm{g}}^{\,i}\ (\mathrm{P}^{i})$ is an estimated gradient vector of $\phi(\mathrm{P})$, in the i times iterative process, P^{i} would be input vector, ϵ^{i} represents observation noise or bias term and perturbation vector. Its step size would be σ^{i} > 0 that can be reduced when the number of iterations increases to make it convergent. The coefficient c^{i} > 0 would be the magnitude of perturbation. In accordance with J, spall suggestions [63], we can select σ^{i} and c^{i} in the form of

$$\sigma^{i} = \frac{\sigma}{(i+1+I)^{\alpha}}\ ,\ c^{i} = \frac{c}{(i+1)^{\gamma}} \tag{5}$$

where $\alpha, \sigma, \gamma\ and\ c > 0\ and\ I \geq 0$ would be for the improvement of convergence of this algorithm.

The gradient approximation would be a Simultaneous Perturbation Stochastic Approximation (SPSA) that jointly and randomly perturbs all elements of P^{i}. In the state of objective function ϕ (P^{i}), it can achieve two different types of perturbed measurements and that can be written as

$$\hat{\mathrm{g}}^{\,i}\ (\mathrm{P}^{i}) = \begin{bmatrix} \frac{\phi\ (\mathrm{P}^{i}+c^{i}\varepsilon^{i})-\phi\ (\mathrm{P}^{i}-c^{i}\varepsilon^{i})}{2c^{i}\varepsilon_1^{i}} \\ \vdots \\ \frac{\phi\ (\mathrm{P}^{i}+c^{i}\varepsilon^{i})-\phi\ (\mathrm{P}^{i}-c^{i}\varepsilon^{i})}{2c^{i}\varepsilon_{\mathrm{K}}^{i}} \end{bmatrix}$$

$$= \frac{\phi\ (\mathrm{P}^{i}+c^{i}\varepsilon^{i})-\phi\ (\mathrm{P}^{i}-c^{i}\varepsilon^{i})}{2c^{i}}\ (\frac{1}{\varepsilon_1^{i}}, \ldots\ldots\ \varepsilon_{\mathrm{K}}^{i}) \tag{6}$$

where $\varepsilon^i \triangleq (\varepsilon_1^i, \ldots \ldots . \varepsilon_K^i)$ is the perturbation vector and $\varepsilon_j^i \in$ {-1, 1} is a random number. In every iteration, we will have two measurements and the size of the vector would be $1 \times K$. If the size of the vector is large, SPSA is effective. Two-measurement complexity might be beneficial as fewer iterations would be required to achieve an optimised value of P^*.

We are proposing an algorithm which can be executed within the Price Control Unit (PCU). We commence the algorithm with an initial value of $\alpha, \sigma, \gamma, P^0$ $and\ I$. At the i^{th} iteration, we update the values in equation (5) and for SPSA, we approximate the value in (6) and accordingly P^i is updated based on (4). In case of maximum number of iterations, the algorithm terminates. When difference between two successive values of the objective function is less than a predetermined threshold this would stop the algorithm.

4.5.3 An algorithm for optimised price

1. Declare the initial value of $\alpha, \sigma, \gamma, P^0$ $and\ I$
2. Repeat
3. Update (5)
4. Update (6)
5. Then update P^i in the (4)
6. Until the stopping criteria

For convergence, we can get updated P^{i+1}= P^i - σ^i $\hat{g}^{\,i}$ (P^i) + ϵ^i where ϵ^i represents observation noise or bias term, according to Y, He, [138] the conditions of the convergence are met. From the pricing algorithm, a user can receive an optimised price value, but it is based on current usage of electricity. However, the EP might update the price value based on demand and industry running cost. Users would receive suggestions based on the selected price value of the energy provider. Every half-hour, based on total load, the EP updates p_t. Accordingly min_t max_t would be updated. The EP selects p_t based on total load and the total running cost of the industry.

4.6 Designing Price Suggestion Unit (PSU)

4.6.1 Problem formulation in the Price Suggestions Unit (PSU)

A Price Suggestion Unit (PSU) is connected to a smart meter that connects to all the user's appliances. The smart meter collects all half-hourly energy consumption real-time data which is passed on to PSU, which make suggestions for the users' based on one day of (48 half-hourly slots') data. This unit suggestions are based on threshold consumption of the user load. The algorithm finds the lowest possible load and makes suggestions for the particular Energy users, balancing the particular time slot of the whole SG. The PSU would expect a response from the user; however, if the user is non-responsive, energy consumption would still be passed on to the Price Control Unit (PCU), and the stochastic price approximation algorithm calculates the price on a real-time basis and generates the price signals to the users. If data is lost at some point, the stochastic method still handles the loss and noise function.

The model [160] is shown in figure 11, where minimising the cost function of demand load in the next upcoming state of the PSU from a user and algorithm developed in the PSU would assist to reduce the peak load. User response would benefit energy suppliers to reduce 'peakers' and, ultimately, industrial cost. The PCU calculates the price based on a user's final consumption. Users would be attracted to respond to the system for the achievement of greater benefit for users and, ultimately, for the whole SG. Our model generates the prices based on 48 time slots, and it optimises the monthly user bill as the model considers an individual's consumption. Every user benefits from the real-time based price generated by the model and essentially, reduces their bill. Peak load has been reduced significantly through the PSU. Final consumption would update the PCU to produce final monthly bills for every individual user.

4.6.2 An Algorithm of the daily Real-Time Price Suggestions

Let us define the buildings as b_1, $b_2 \ldots$ b_n, and time slots are defined as t_1, $t_2 \ldots$ t_p

We can have the matrix as

$$\begin{pmatrix} b_1 t_1 & \cdots & b_1 t_p \\ \vdots & \ddots & \vdots \\ b_n t_1 & \cdots & b_n t_p \end{pmatrix} \quad (7)$$

Make a summary matrix for each building with all time slots

$$\begin{pmatrix} \sum_{i=1}^{48} b_1 t_i \\ \vdots \\ \sum_{i=1}^{48} b_n t_i \end{pmatrix} \quad (8)$$

Another summary matrix for each time slot with all buildings

$$\left[\sum_{j=1}^{n} b_j \, t_1 \; \ldots\ldots. \; \sum_{j=1}^{n} b_j \, t_{48} \right] \quad (9)$$

Make an average matrix for each building with all time slots

$$\begin{pmatrix} (\sum_{i=1}^{48} b_1 t_i) / 48 = a_1 \\ \vdots \\ \sum_{i=1}^{48} b_n t_i / 48 = a_n \end{pmatrix} \quad (10)$$

And another average matrix for each time slot with all buildings

$$\left[\frac{\sum_{j=1}^{n} b_j t_1}{n} \ldots\ldots\ldots\ldots\ldots\ldots \frac{\sum_{j=1}^{n} b_j t_{48}}{n} \right] \quad (11)$$

Overall average = $\frac{\sum_{j=1}^{n} \sum_{i=1}^{48} b_j t_i}{n}$ (12)

Make a surplus matrix for each building with all time slots

$$\begin{pmatrix} b_1 \sum_{i=1}^{48} t_i - \sum_{i=1}^{48} a_{1i} \\ \vdots \\ b_n \sum_{i=1}^{48} t_i - \sum_{i=1}^{48} a_{14i} \end{pmatrix} \tag{13}$$

As to make changed position matrix from equation 7, we will make a surplus if

$$\begin{pmatrix} (b_1 t_1)_c & \dots & (b_1 t_{48})_c \\ \vdots & \ddots & \vdots \\ (b_n t_1)_c & \cdots & (b_n t_{48})_c \end{pmatrix} \tag{14}$$

where

$(b_1 t_1)_c = b_1 t_1 - a_1$, $(b_1 t_2)_c = b_1 t_2 - a_1$ …………… $(b_1 t_{48})_c = b_1 t_{48} - a_1$

$\vdots$

$(b_n t_{48})_c = (b_n t_{48}) - a_n$, $(b_n t_2)_c = (b_n t_2) - a_n$ ……. $(b_n t_{48})_c = b_n t_{48} - a_n$

subject to $b_1 t_i > a_1$ $b_n t_i > a_n$, where $i = 1,2 \dots \dots \dots \dots \dots . . 48$

There are some conditions to consider, such as every element of the changed matrix is determined to compare to a total load of each time slot with all buildings that must be less than the overall average load. It finds the lowest possible load in all elements of the changed matrix. Then the algorithm starts from the lowest changed element of the lowest total load per time slot. It checks with the particular building average. Then it fills the load in the lowest position and makes a surplus load matrix if it exceeds the average load of the particular time slot. Again, check another lowest load position.

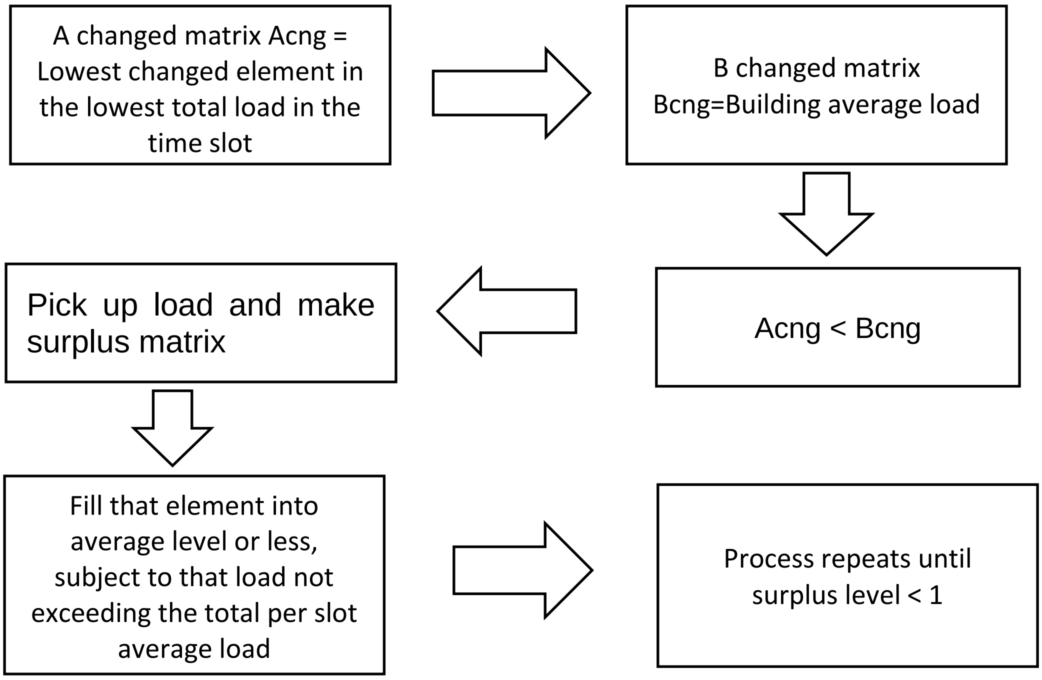


Figure 13: Proposed pricing model process explained

If necessary, it takes the load from the relevant surplus position. Then, it fills the load to the particular position and makes it into the average level, subject to the total amount of a load of that particular time slot that would not exceed the overall average load. Re-organise the latest changed matrix; process two repeats until the element of surplus matrix < 1, which we call an insignificant adjustment amount.

We find sum of per building time slots or total energy consumption per day:

$$= \sum_{t=1}^{p} b_n\, t_p \qquad (15)$$

Sum of total building consumption per time slot

$$= \sum_{b=1}^{n} b_n\, t_p \qquad (16)$$

Find per building per slot average

$$= \frac{\sum_{t=1}^{p} b_n t_p}{p} \qquad (17)$$

Total building per slot average

$$= \frac{\sum_{b=1}^{p} b_n t_p}{n} \qquad (18)$$

Find peak load from every time slot in each building in time slot b_1t_4, Find peak load from all buildings overall, for example in time slot t_4, peak of t_1, $t_2 \ldots t_p$. The algorithm process is as follows:

Process 1: If b_1t_1 > average of b_1 load then adjust the load, otherwise go to the next slot and calculate how much load extra, then fill in separate slot t_p. Check b_1t_1 < average of b_1 load, if it is yes, then leave and check another one.

Process 2: Overall check: If any time slot has more than average then fill in the separate slot Ot_p

Process 3: Check building basis per time slot load, again if less than average load then take a load from t_p, fill that load subject to check if overall load < average overall load. Then fill that time slot from t_p, otherwise, leave the slot and check the next slot.

Process 4: Calculate the overall time slot load and check with the overall Ot_p load.

The flow chart in figure 15 shows the how the algorithm works at a glance.

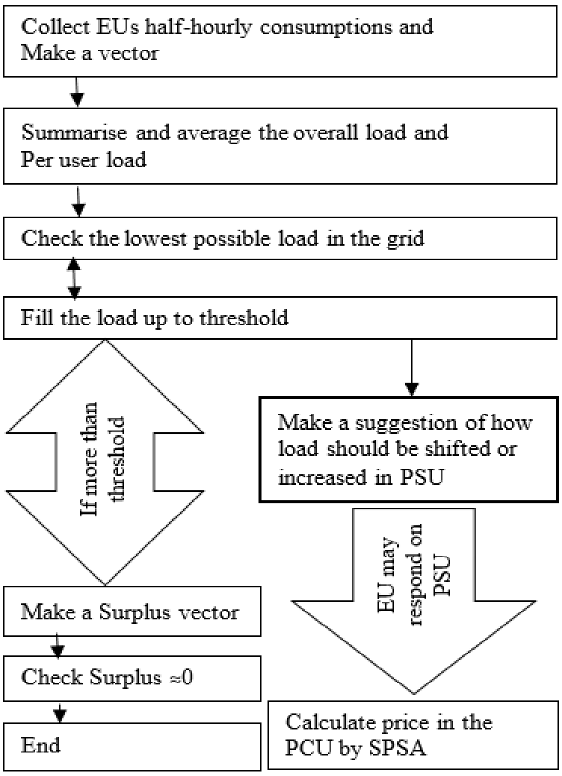


Figure 14: Proposed pricing algorithm working procedure

4.6.3 Process involved with the price suggestions

All buildings' half-hourly data makes a matrix of the number of buildings by 48 time slots. We count an average load for each of the buildings. On a half-hour basis, we checked the lowest load irrespective of all buildings. We filled that load trying to match with the particular building average load.

If that load is greater than the particular building average then it filled with the average load, otherwise the load will not be changed, it would be kept as it is. Thus we can make another matrix that is called the surplus matrix where the extra load is kept, as we filled that load to the average load.

Now, after doing this iterative way, we try to find out the lowest possible value in the whole matrix. We compare with the average load so that it should not exceed the average load during filling up the load and compare with the surplus matrix and adjust the surplus matrix.

We then checked the latest changed matrix of the original half-hourly matrix with the minimum overall load. This changed matrix needs to meet some conditions. If the latest changed matrix is less than any building's lowest load, not zero and less than average load of that particular building, then fill up the load up to the average load. One of the most important aspects of this algorithm is that it avoids the places already visited and changed at least one time.

Obviously, it would visit the total amount of a load of every time slot in each iteration and check that it must not exceed the overall average load in the SG. We save the extra load that is the difference between the total loads, in a particular time slot and the overall average load.

Again, check that the load in both time slot and building bases. Check the particular lowest load of the latest changed matrix is less than the average load of the building and the difference between total loads in the particular time slot and the overall average load is greater than the average, then fill the load. Otherwise, check the extra load adding with the original load is greater than the average load then fill the load. Otherwise, the original load would be equal to the extra load plus the original load.

This process would continue iteratively until all buildings' load the average level of each of the buildings. This process would bring the overall average load in the SG. We can find the ideal load shift once we deduct the original load from the latest average level load.

A Price Suggestion Unit (PSU) is connected to a smart meter that connects to all appliances. The smart meter collects all half-hourly energy consumption real-time data that passes on to the PSU which make suggestions for the users' based on one-day (48 half-hourly slots) data. This unit suggests based on threshold consumption of the user load. The algorithm finds the lowest possible load and makes suggestions for the particular Energy users, balancing the particular time slot of the whole SG. The PSU would expect a response from the user, however, if the user is non-responsive, energy consumption would still be passed on to the Price Control Unit (PCU), and the stochastic price approximation algorithm calculates the price on a real-time basis and generates the price signals to the users. The stochastic method would handle the loss and noise function. The model [160] is shown in figure 11, where minimising the cost function of the demand load in the next upcoming state of the PSU from a user and algorithm developed in the PSU would assist to reduce the peak load. User response would benefit energy suppliers to reduce 'peakers' and, ultimately, industrial cost. The PCU calculates the price based on a user's final consumption. Users would be attracted to respond to the system for the achievement of greater benefit for users and, ultimately, for the whole SG. Our model generates the prices based on 48 time slots, and it optimises the monthly user bill as the model considers individual consumptions. Every user benefits from this real-time based price generated by the model and essentially, reduces their bill. Peak load has been reduced significantly through the PSU. Final consumption would update the PCU to produce final monthly bills for every individual user.

4.6.4 An algorithm for the monthly suggestions

We denote the user's building B as b_1, $b_2 \ldots b_m$, day as d defined as d_1, $d_2 \ldots d_q$, where every day is divided into l number of time slots of the time T as t_1, $t_2 \ldots t_l$ where $t \in T$, $b \in B$ and we can have the matrix as

$$\begin{pmatrix} b_1 d_1 t_1 & \ldots & b_1 d_1 t_1 \\ \vdots & \ddots & \vdots \\ b_m d_q t_1 & \cdots & b_m d_q t_1 \end{pmatrix} \tag{19}$$

Producing a summary matrix for each independent building user for the time slots

$$\begin{pmatrix} b_1 d_1 \sum_{l=1}^{48} t_l \\ \vdots \\ b_m d_q \sum_{l=1}^{48} t_l \end{pmatrix} \tag{20}$$

where $l = 1,2 \ldots 48$, $m = 1,2, \ldots n$, $q = 1,2, \ldots 30$

Defining the summary matrix as

$$\left[\sum_{m=1}^{n} b_m \, d_1 t_1 \; \ldots \; \sum_{m=1}^{n} b_m \, d_q t_{48} \right] \tag{21}$$

The average over a month matrix as

$$\begin{pmatrix} \dfrac{\sum_{m=1}^{n} \sum_{q=1}^{30} \sum_{l=1}^{48} b_m d_q t_l}{30x48} = a_1 \\ \vdots \\ \dfrac{\sum_{m=1}^{n} \sum_{q=1}^{30} \sum_{l=1}^{48} b_m d_q t_l}{30x48} = a_m \end{pmatrix} \tag{22}$$

Every time slot produces an average matrix as

$$\left[\frac{\sum_{m=1}^{n} b_m \, d_1 \, t_1}{n} \ldots \frac{\sum_{m=1}^{n} b_m \, d_q t_{48}}{n} \right] \tag{23}$$

The overall building basis average is $\dfrac{\sum_{m=1}^{n} \sum_{q=1}^{30} \sum_{l=1}^{48} b_m d_q t_l}{n}$ (24)

Every building produces a surplus matrix as

$$\begin{pmatrix} b_1 d_1 \sum_{l=1}^{48} t_l - \sum_{l=1}^{48} a_{1l} \\ \vdots \\ b_n d_q \sum_{l=1}^{48} t_l - \sum_{l=1}^{48} a_{ml} \end{pmatrix} \quad (25)$$

Producing a change position matrix from the first matrix as

$$\begin{pmatrix} (b_1 d_1 t_1)_{ch} & \dots & (b_1 d_1 t_{48})_{ch} \\ \vdots & \ddots & \vdots \\ (b_m d_q t_1)_{ch} & \cdots & (b_m d_q t_{48})_{ch} \end{pmatrix} \quad (26)$$

where

$(b_1\ d_1 t_1)_{ch}$=$b_1\ d_1 t_1$- a_1, $(b_1\ d_1 t_2)_{ch}$ = $b_1\ d_1 t_2$- a_1 .. $(b_1\ d_1 t_{48})_{ch}$ = $b_1\ d_1 t_{48}$- a_1

Subject to $b_1\ d_1 t_l$ > a_1

⋮

$(b_m\ d_q t_{48})_{ch}$=$(b_m\ d_q t_{48})$-a_m,$(b_m\ d_q t_2)_{ch}$=$(b_m\ d_q t_2)$-a_m..$(b_m\ d_q t_{48})_{ch}$=$b_m\ d_q t_{48}$-a_m

subject to $b_m\ d_q t_l$ > a_m (27)

The sum total of the each user's time slots is defined as

$$= d_q t_l \sum_{m=1}^{n} b_m \quad (28)$$

where $l = 1,2 \ldots 48$, $m = 1,2, \ldots n$, $q = 1,2, \ldots 30$

The total sum of energy usages in each time slot is

$$= b_m d_q \sum_{l=1}^{48} t_l \quad (29)$$

where $l = 1,2 \ldots \ldots .. 48$, $m = 1,2, \ldots . n$, $q = 1,2, \ldots 30$

Every user threshold load is calculated as

$$= \frac{d_q t_l \sum_{m=1}^{n} b_m}{m} \quad (30)$$

Every time slot-threshold load is defined as

$$= \frac{b_m d_q \sum_{l=1}^{48} t_l}{30x48} \quad (31)$$

By considering each user's threshold load, the algorithm checks the lowest possible load from all users without exceeding the threshold load in each time slot of the whole grid. The algorithm suggests in the PSU. It has been explained in two flowcharts in figures 14 and 15. The flowchart in figure 16 shows the proposed structural model. It explains the whole procedure involved with the RTPS model.

4.7 Flowchart of the proposed structural model

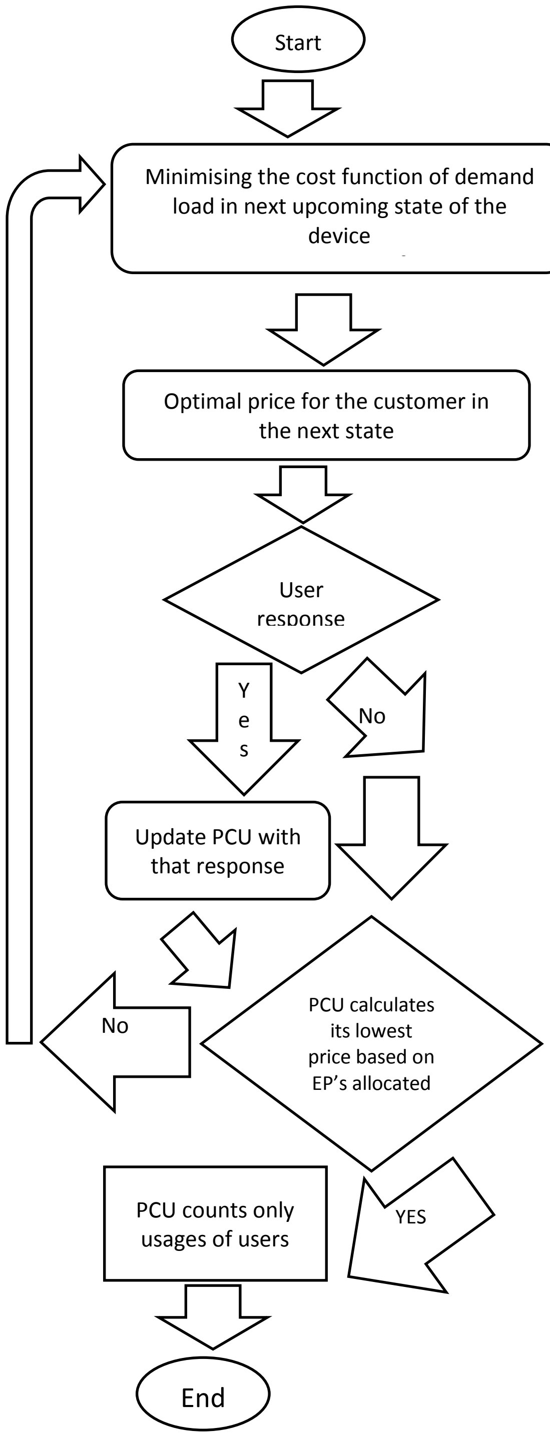


Figure 15: Proposed model's flow chart

From the pricing algorithm, a user can receive an optimised price value, but it is based on current usage of electricity. However, the EP might update the price value based on demand and industry running cost. Users would receive suggestions based on the selected price value of the energy provider. Every half-hour, based on total load, the

EP updates p_t. Accordingly min_t max_t can be updated. The EP selects p_t based on total load and the total running cost of the industry.

Users are equipped with a smart meter and the Energy Supplier communicates their price by using a Local Area Network. The Price Suggestion Unit informs the user's optimal usage plan and their actual usages so that they can be aware of what they are approaching to spend. An Energy user may use IoT-enabled devices so that the PSU unit and smart meter can collect data using a sensor. We have checked with the monthly basis price reduction with a high volume of data dimensionality [161], it has given a significant result. It manages to reduce the bill and cost of energy distribution for the users as well as energy providers, simultaneously.

4.7.1 Collecting user responses to PSU

The suggestion displays in the Price Suggestion Unit for the users who need to follow the suggestions to reduce their bill. This algorithm reduces the Peak-to-Average Ratio (PAR) from the EP point of view whilst at the same time a user response counts and calculates their prices on a real-time basis. In this algorithm, we simulate the user response, for example, they follow 20% of the suggestions. We measured their response and produced a result that shows PAR is reduced and users' experience bill savings when compared to a flat-rate pricing solution.

Every user has appliances that are running continuously, non-flexible and flexible. Moreover, users have different types of priorities to shift their load as per suggestions from the PSU. We assume that they have three types of appliances that are running. Regarding priority, we assume that for the first type of appliances, users may prefer to shift the load. The second type of preferences would be a lower priority. The third type is the non-flexible appliances, which would not be a priority for the users to shift their load.

Non-flexible appliances are those like refrigerator, light and kettle. Flexible appliances are air-conditioning units, iron, PC, TV and are most essential, but the user may shift load on a priority basis, for electric cooker, clothes dryer and vacuum cleaner would be a second priority basis. For the last priority, the user may have a schedule for pool pump, water heater, heater, hairdryer, dishwasher, PEV and geyser. The user would shift their load flexible appliances based on their necessities to maximise their satisfaction; at the same time, they would minimise their energy bill.

4.7.2 How EP can decide on their price

On a real-time, every half-hourly basis a unit price would be suggested for the users in the PSU. Our model will address the 24-hour base price suggestions and collect user responses through the PSU. In the PCU, the EP would calculate their average cost based on the Peak-to-Average (PAR) load that is calculated from the daily peak load divided by the daily average load and that would be our objective function, written as

$$\min_{u \in U} PAR = \frac{T \max\{l_1 \ldots\ldots\ldots l_T\}}{\sum_{t=1}^{T} l_k} \quad (32)$$

Where l_t is the total energy usage of a user at time slot k. T_{max} $\{l_{1 \ldots\ldots} l_T\}$ is the user's peak load and T = 48. An EP will calculate their price based on their hourly-basis total industrial running cost, which could be calculated from their business point of view. The running cost can be calculated on five years' infrastructure investment and the day-to-day administration cost. At this stage, we are defining a variable rc that would be considered as the hourly basis running cost. Now, we need to find out the energy unit price from the EP perspective, which can be defined as

$$p_t = \frac{\sum_{u=1}^{U} PAR}{rc} \quad (33)$$

where p_t = energy unit price from EP in PCU, rc = per half-hourly industrial running cost. However, the EP can make a profit based on demand calculated from users. At this stage, we have considered the current market flat-rate price and random fluctuation around the flat-rate price that has been charged on a real-time basis in every time slot in our dataset. We can calculate the user-side total energy consumption and inform the EP by bi-directional communication. Then the EP calculates the demand response within price vector P. Our target is to maximise the user's satisfaction by reducing their bill and at the same time minimising the EP's cost and by doing those, obviously, we will be able to reduce PAR.

4.7.3 Price Suggestion Unit (PSU) interface for users

The user will be notified via a user interface by using a browser on their PC or in the PSU itself. The message should be advised to users. For example, there would be instructions to the user that they should shift their flexible appliances' load. Their price would be based on the price allocated by the EP. Their actual price at that moment would be the actual price calculated based on the optimised price calculated by the SPSA algorithm based on usage. From the EP, the slot can be suggested for the users to shift their load based on historical data like slot 3-5, 6-9, 3-12 etc. The data we have received would be modelling a pattern of 30 days' data per time slot, which would be predicted in the next time slot with the adjustment of the load shifting value.

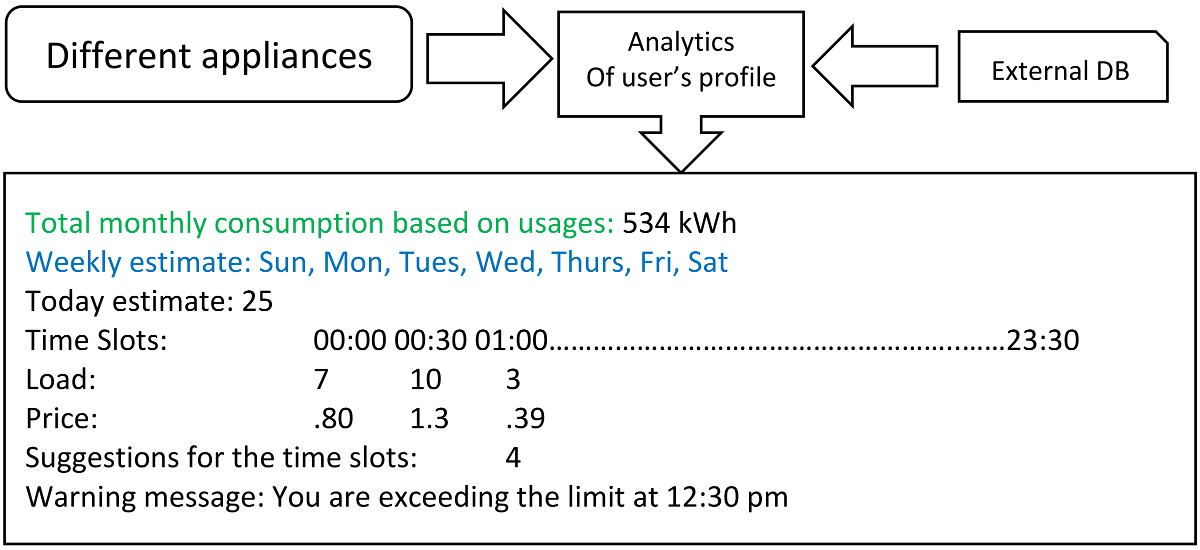


Figure 16: Proposed Price Suggestion Display Unit

The user interface would help the user to decide which time slot would be useful for them to shift their load based on suggestions. The architecture of Yupik [162] suggested the use of a Gantt chart displayed through a website browser or mobile smartphone app. However, we would have a GUI for the interface that would provide the proposed time of use per slot, how much cost would be incurred based on the load, actual current usages of appliances, cost incurred based on current usages, daily cost and prediction of monthly basis cost incurred and different features would be shown using a different colour.

A user can choose non-flexible appliances to deviate from suggestions. If a user exceeds the limit of the budget, it will show as red, and it would indicate that the user is outside the optimal estimate. The Price Suggestion Unit informs the user's optimal usage plan and their actual usage so that they can be aware of what they are approaching to spend. An Energy user may use IoT-enabled devices so that the PSU unit and smart meter can collect data from sensors. Considering the growing number of customers, we need to analyse the huge amount of data to make this efficient. We can use data mining techniques WEKA and CPLEX to solve different levels of problem. Moreover, all this display would be in mobile apps so that user should act by looking at mobile warning.

4.7.4 Future research process with a smart appliance

On the user side, how does the schedulable algorithm work: in figure 18, user side the schedulable appliances flowchart provides an outline of how the user-side Price Suggestion Unit would work and how user responses would be integrated into that working process. This aspect of the research is still under development. Our model fits on the current state of the SG. However, it would be possible to fine tune the model if all smart appliances in the market. User may take their decision based on their appliances flexibility which is shown below.

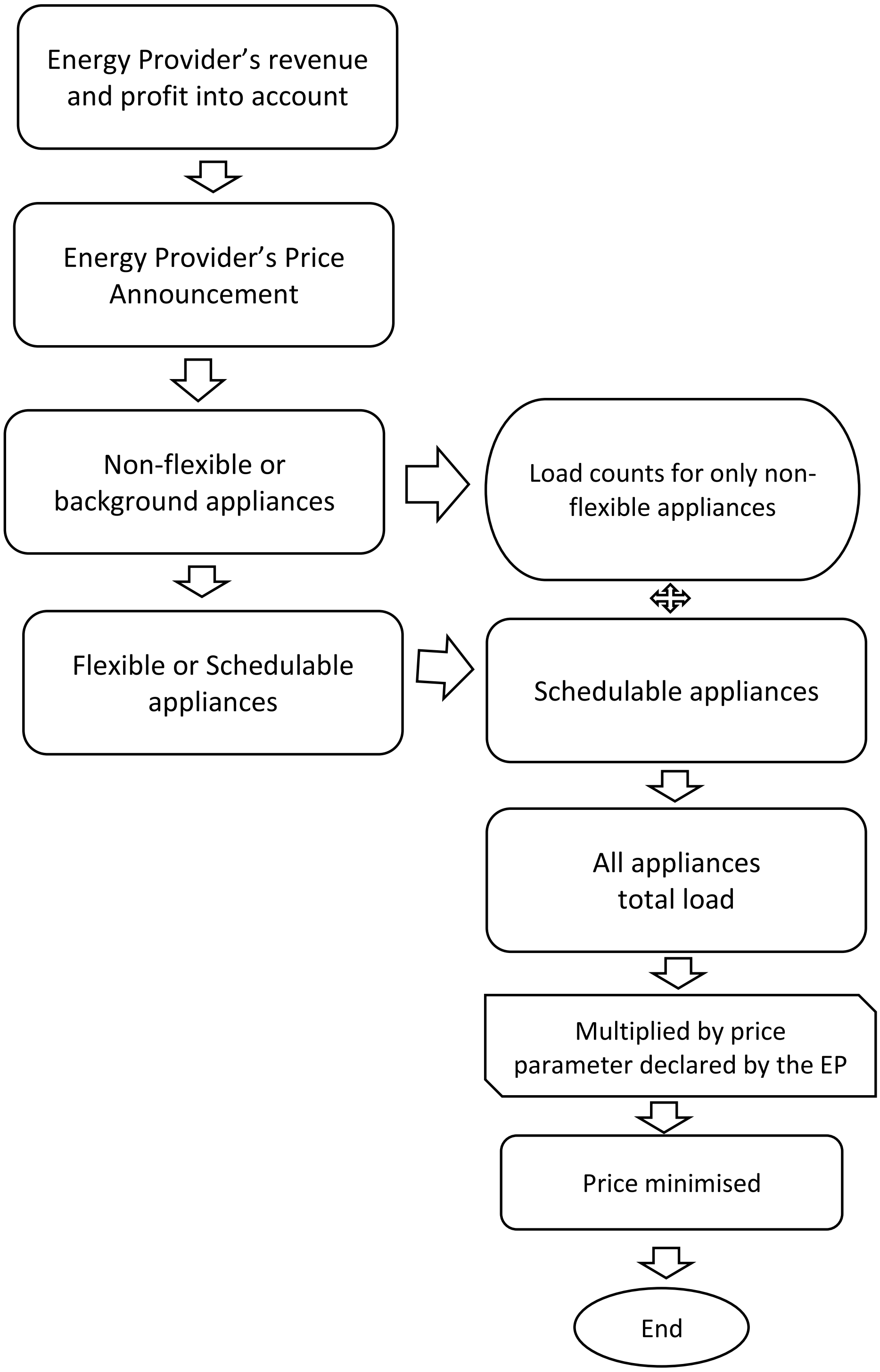


Figure 17: User-side smart appliances flowchart

4.7.5 Future research with multiple energy providers' energy distribution

Different countries have different arrangements; however, according to National Institute of Standards and Technology (NIST) [10], they have a model of electricity distribution, almost similar to the UK: energy distributors are connected to the main power grid, and all of the users are also connected to the power grid. With the current arrangement, if any customer changes distributor or energy provider, they do not need to do anything except notify the power grid, and they will organise the distribution change. No infrastructure arrangement needs to be changed.

We are planning to integrate multiple energy providers within our model so that we can develop a more comprehensive and robust model. Currently, power generation transmission to the distribution centre and eventually, all Energy Providers are distributing energy to users from the same distribution centre for their customers. Thus, customers would be different for different EPs. The conceptual idea is as follows in figure 19 below. Our model will address the multiple energy providers' accumulated energy distribution. Eventually, the generation centre would reduce the load as a whole. Initially, RT pricing assists the customer's price reduction and shifting load from single EP. We can fine- tune the model to integrate the multiple EP.

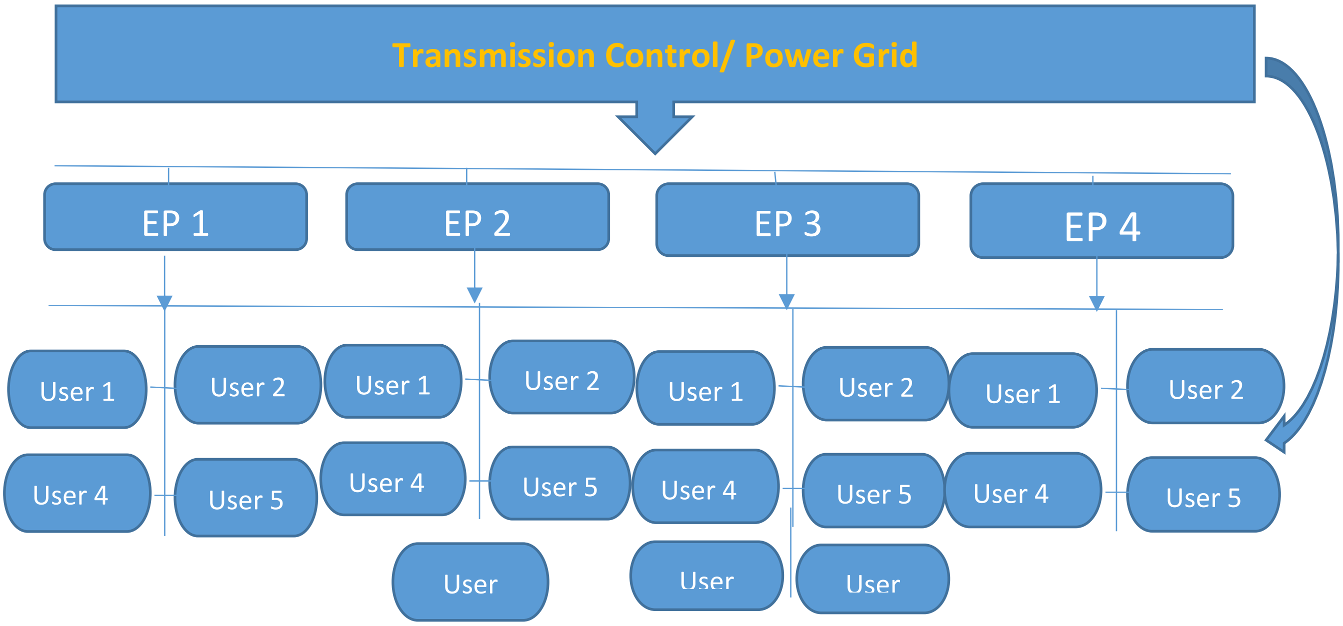


Figure 18: **Multiple EPs integration planning flowchart**

4.8 Summary of the proposed models

This research focused on developing a model with the notable contribution of the Real-Time Price Suggestion (RTPS) model with a Price Suggestion Unit (PSU) connected with a Price Control Unit (PCU) for real-time demand response in the SG. In this chapter, we explained how the proposed model is formulated and would work with a mathematical algorithm which is developed for the Price Suggestion Unit (PSU) and Price Control Unit (PCU). Subsequently, it uses stochastic approximation methods to generate prices and provide suggestions for users for when they should shift their load. We have given an architectural overview in figure 13 of how all the devices are connected to produce the optimised price for users.

Eventually, they shift their load and help to reduce the Peak-to-Average Ratio (PAR) and the users' bill. The more they shift load according to suggestions, the more benefit is achieved. However, all Energy Users' (EU) and energy providers' rights are protected to ensure the optimised lower price when compared to the traditional flat-rate price, even when most of the users are unresponsive to the system. The EP can reduce the PAR, and we provide a detailed discussion in the experiment and result chapter (Chapter 5) that explains how the costs are saved. This model can be extended with multiple energy providers' perspectives, which also has been given as an idea as a future research direction (Chapter 6).

5 Experiment and Implementation Results

In this chapter, we illustrate the performance of the system which is equipped with an algorithm for price suggestion unit and price control unit. With the algorithm implemented in the system, we delineate the overall experimental result and test the system. Particularly, the result shows how the system benefits all buildings and energy providers. We checked the results based on a daily and monthly data. Our results show that Energy users saved significant costs and the overall Peak-to-Average Ratio (PAR) was also reduced which is of benefit to energy providers.

Using the optimisation technique, the system generates total prices using a flat-rate price Time-of-Use (TOU) approach and it also generates a real-time (RT) price. The system uses minimum, maximum prices on a real-time basis. We used half-hourly data as per our available dataset. It could also be fine-tuned to consider smaller units of time if necessary. Our dataset is the half-hourly basis and consequently, we analysed our model on a half-hourly basis.

We decompose the whole analysis into four different categories. Firstly, we analysed how buildings as a whole are consuming energy and how an individual building is using its energy. Secondly, we consider how the overall flat-rate price is implemented in the grid and also as part of an individual building's flat-rate price analysis. This analysis is divided into two categories: one is a daily basis, and the other is the monthly basis. Both have two different algorithms as discussed in Chapter 4.

We implemented a real-time (RT) based pricing analysis on the daily and monthly basis. By considering our model, we analysed the case without considering the user's response price calculation and also analysed the other case by taking 20% of users' responses into consideration. Thirdly, we endeavour to show how users made cost savings with the consideration of flat-rate and Real-Time Pricing. We have also shown how RT price selection can be applied to every building. Fourthly, we have shown how the Peak-to-Average Ratio (PAR) is reduced on the EP side where they can reduce their cost by reducing their overall peak load, which is very significant for them as the EP's cost depends on overall peak demand from energy users. We have shown the daily price suggestions where the user needs to shift their load to save their money. Our data is based upon daily data divided into 48- time slots (one every half-hour) for energy consumption that is shown in detail in figure 120. To check data validation, we launched an analysis using Principal Component Analysis (PCA) in figure 157. The buildings are not similar: they are very diverse, some of them small, medium or large. It shows that our model accommodated the high variability of data. In this chapter, all the various analysis and results are presented.

5.1 Daily pricing analysis

5.1.1 Energy Providers' price from the transmission control

The national power grid is designed comprehensively from electricity transmission to distribution. After energy generation, electricity is transmitted with high voltage to distribution centres, but prices are usually controlled centrally. On a half-hourly basis, the price of electricity is based on demand from different distributors who are referred to as EP. Main transmission control does not charge household energy users directly. Main power grid transmission control charges the EP in each time slot based upon its peak demand from users in the particular time slot. The price suggested depends on the energy providers' peak distribution; they are sometimes referred to as 'peakers'. Therefore, it is very significant that EP needs to concentrate on the Peak-to-Average Ratio (PAR). This is how the whole process is defined from load distribution to pricing. We have performed a test based on our data from the University of Bedfordshire (UoB) and Department for Education (DfE). We have performed some of the analysis relating to the DfE separately for the time-varying DfE building data and similarly for the UoB.

5.1.2 Load variation in different buildings

There are four buildings from DfE and ten buildings from the UoB. We have illustrated the four DfE buildings, which shows in figure 20 (Appendices) that they have continuous (over 24 hours) energy consumption. Each of the buildings has data based upon a half-hourly basis (48- time slots per 24 hours) where employees are consuming energy, mostly in office time, but there are usages of energy throughout the whole day. The variations of the consumption for all four buildings are shown in figure 155. The Sanctuary building has the highest consumption, whereas Castle View House has the lowest consumption. The remaining two buildings have similar consumptions. The graphical representation in figure 20 (Appendices) shows building consumption across the different time slots. Almost all of the buildings (Sanctuary, Castle View House, Mowden Hall, St Pauls Place) show that in the middle of the day, mostly 11.30 am to 15.00, consumption is high.

Figure 21 (Appendices) shows how the UoB buildings' energy load is distributed. Some of the buildings have many spikes: this means buildings have varied energy consumption. The buildings have diverse levels of energy consumption. Different buildings have various load distribution scenarios over the whole day. The buildings do not all follow the same pattern. Some of them have higher load consumption in the middle of the day, some of them have evenly distributed load pattern, some of them have an uneven load consumption pattern.

We have analysed 14 buildings together (two institutes), where some of the buildings consume their energy high across the middle of the day. However, some of the buildings consumed almost similar energy consumption across the entire 24-hour period. This scenario shows that we cannot assume the buildings' consumption will align to standard business working hours. Every building or user is different. To ensure a balanced supply regarding demand, energy providers need to rely on overall peak energy consumption.

In the industrial scenario, we may find a different load consumption scenario. In conclusion, we have to admit a variety of energy use scenarios. We have tested our algorithm on these 14 buildings. The graphical representation in figure 22 shows all the buildings and how they consumed their energy in different slots. Building 1 represents a very large building that consumed a large amount of energy per day; the remaining buildings are significantly smaller and their energy consumption in different slots can be seen. In figure 22 shows all buildings consumption on a time slot basis.

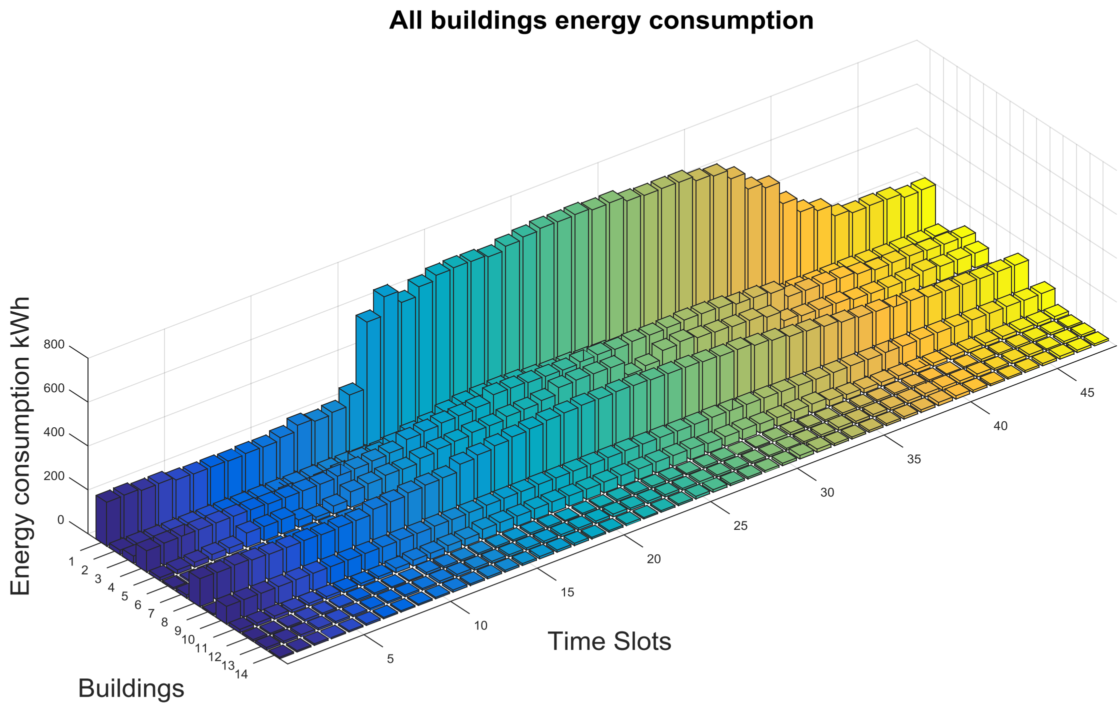


Figure 19: Energy consumption in 48 half-hourly time slots for 14 different buildings

We have analysed total loads for four buildings in figure 23 (Appendices) for DfE: we have found the small buildings consumed, on average, 1291 kWh, the biggest building consumed 20,480 kWh, and their average (across all four buildings) consumption is 8147 kWh. The other two buildings consumed 3906 kWh and 6916 kWh. So, the average demand from the data we have that is 8147 kWh. For UoB in figure 24 (Appendices), the smallest building usage was 364.5 kWh, the biggest building usage was 8563 kWh and their average demand is 2153 kWh. The remaining building usages are 4714, 732, 387, 4048, 1413, 382, 486, 439 kWh, respectively.

5.1.3 Energy providers' supply regarding users' demand in different time slots

We have measured institutes, individual buildings and overall demand and supply. The graphical representation in figure 25 (Appendices) shows that the overall demand at the DfE is 32,588 kWh. However, the average consumption per time slot is 678.9 kWh, where peak demand is 1073.5 kWh and minimum demand is 322.3 kWh. From an energy providers' point of view, the graphical representation in figure 26 (Appendices) for the UoB buildings shows that the total average demand from all users is 448.5

kWh, total demand from users 21,529 kWh and peak demand of 648 kWh in time slot number 26 which is 12.30 pm. The minimum demand from the UoB is 274 kWh.

From an energy providers' point of view, how should an EP view its supply regarding users' demand. The graphical representation (figure 27) shows that the total average demand from all users is 1127 kWh, total demand from users 54,117 kWh and peak demand of 1702 kWh in time slot number 25 which is 12 pm. The minimum demand for all DfE and UoB 14 buildings is 604.4 kWh.

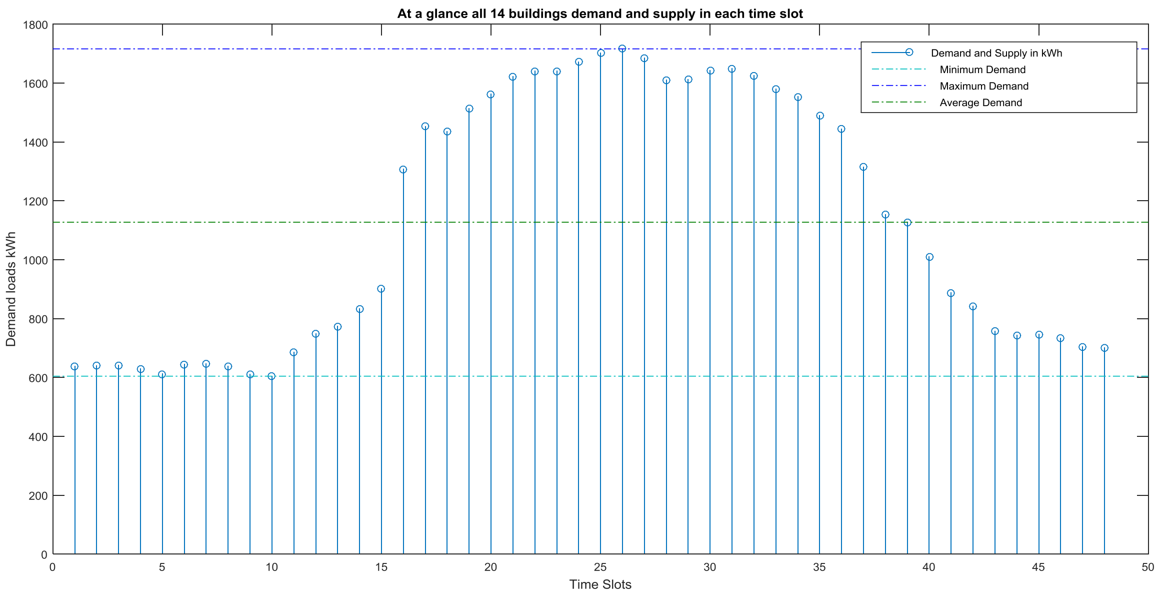


Figure 20: **Users' demand from all 14 buildings in each time slots.**

5.1.4 Individual building based demand-supply analysis

We generated a different graphical representation of each different building's load. It is significant to show that every building has a different load pattern. Individual building based analysis is shown in the different figure below. The figure 28 shows that in Sanctuary, 426.56 kWh is the average load, its peak load 691 kWh; the lowest load is 174 kWh. The total load in the Sanctuary building is 20,475 kWh.

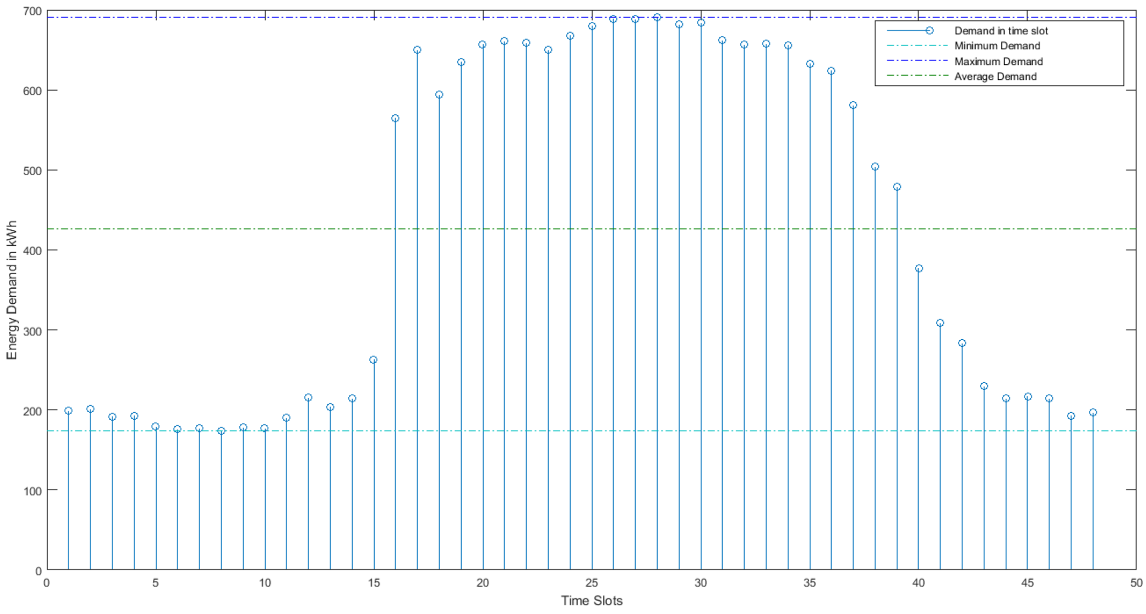


Figure 21: **Energy load distribution in the Sanctuary building**

We generated the Castle View House load in figure 29 (Appendices) where it shows that in Castle View House the average load is 26.89 kWh, its peak load is 38.6 kWh, and the lowest load is 18.4 kWh. Total Castle View House load is 1290.8 kWh.

The graphical representation in figure 30 (Appendices) shows that the minimum load in Mowden Hall is 32.4 kWh, peak load is 162.1 kWh and average load is 81.4 kWh. The total Mowden Hall load is 3906 kWh.

The graphical representation in figure 31 (Appendices) shows the minimum load in St Pauls Place is 95.6 kWh, peak load is 207.4 kWh, and the average load is 144.1 kWh. The total St Pauls Place load is 6915.8 kWh.

In the UoB Campus building (figure 32), the minimum consumption is 14 kWh, maximum consumption is 185.5 kWh, and average consumption is 98.2 kWh. There are variations in different time slots; some spikes show that sometimes energy consumption dropped suddenly from 13.30 to 14.30, and we do not the reason.

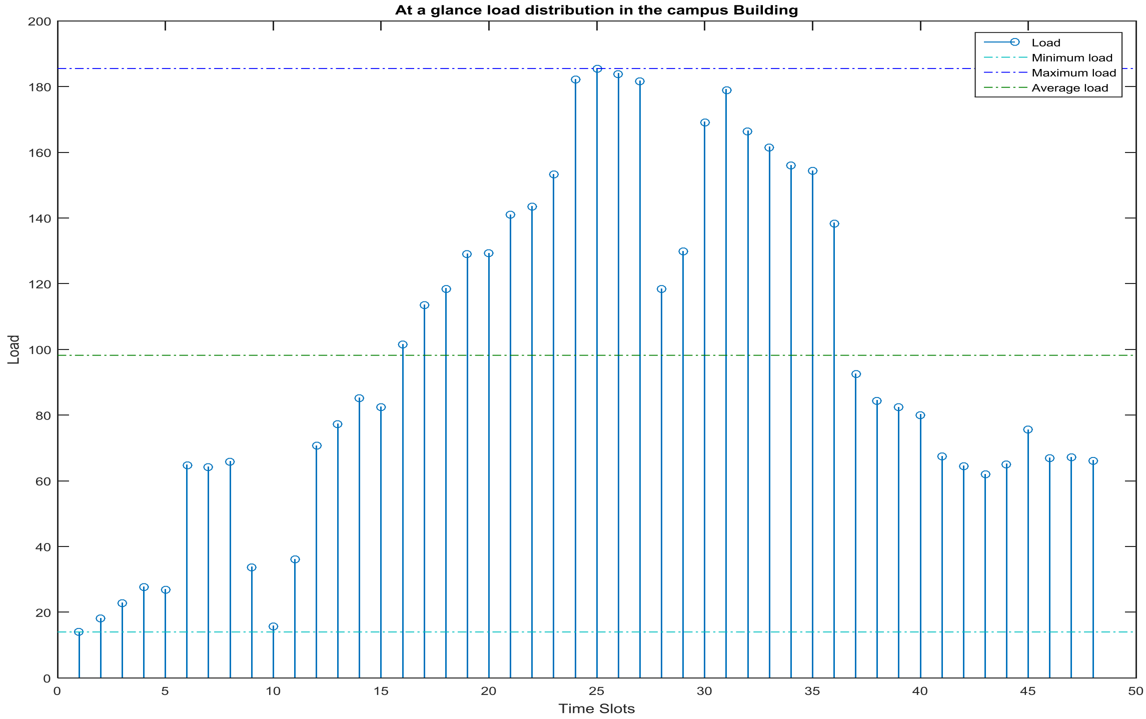


Figure 22: **Load distribution in the Campus Building**

In the Johnson building of UoB (figure 33), the lowest consumption measured is 4.8 kWh, the maximum load measured is 7.6 kWh and peak load measured is 15.1 kWh. Load in different time slots do not follow a normal distribution.

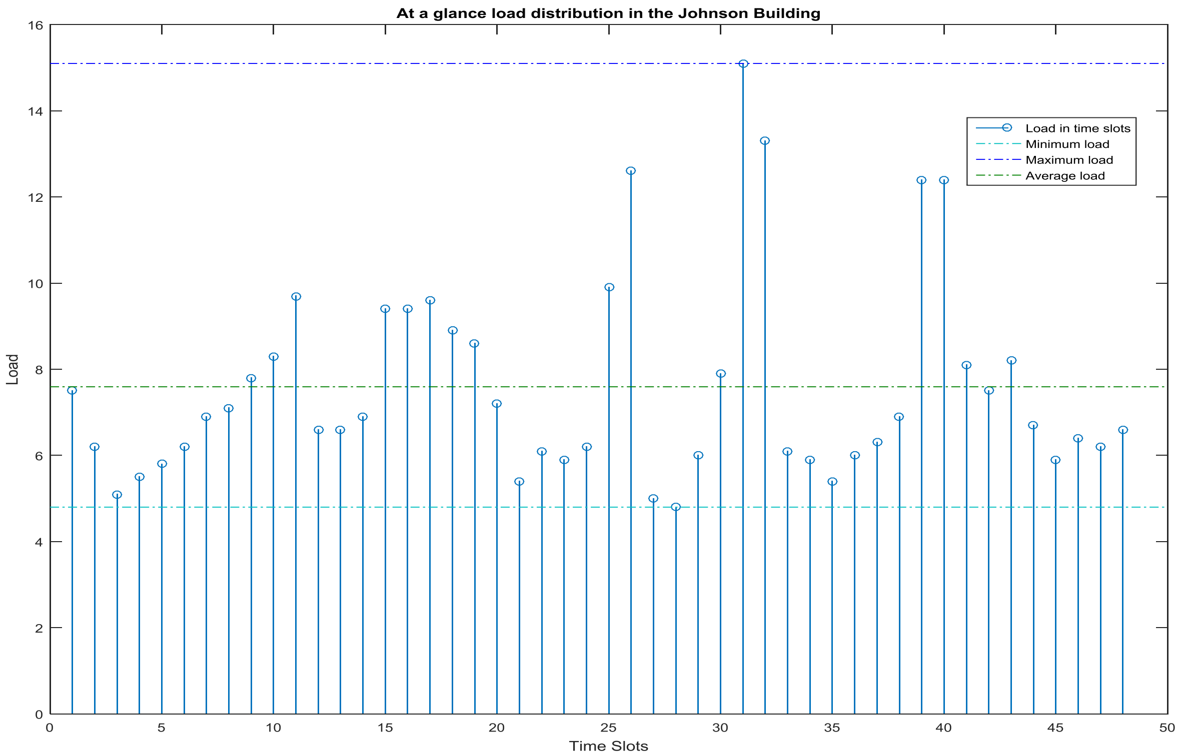


Figure 23: **Load distribution in the Johnson Building**

In the Lidle building of the UoB (figure 34), the lowest consumption measured is 9.6 kWh, the maximum load measured is 23 kWh and peak load measured is 15.3 kWh. Load in different time slots do not follow a normal distribution, as well.

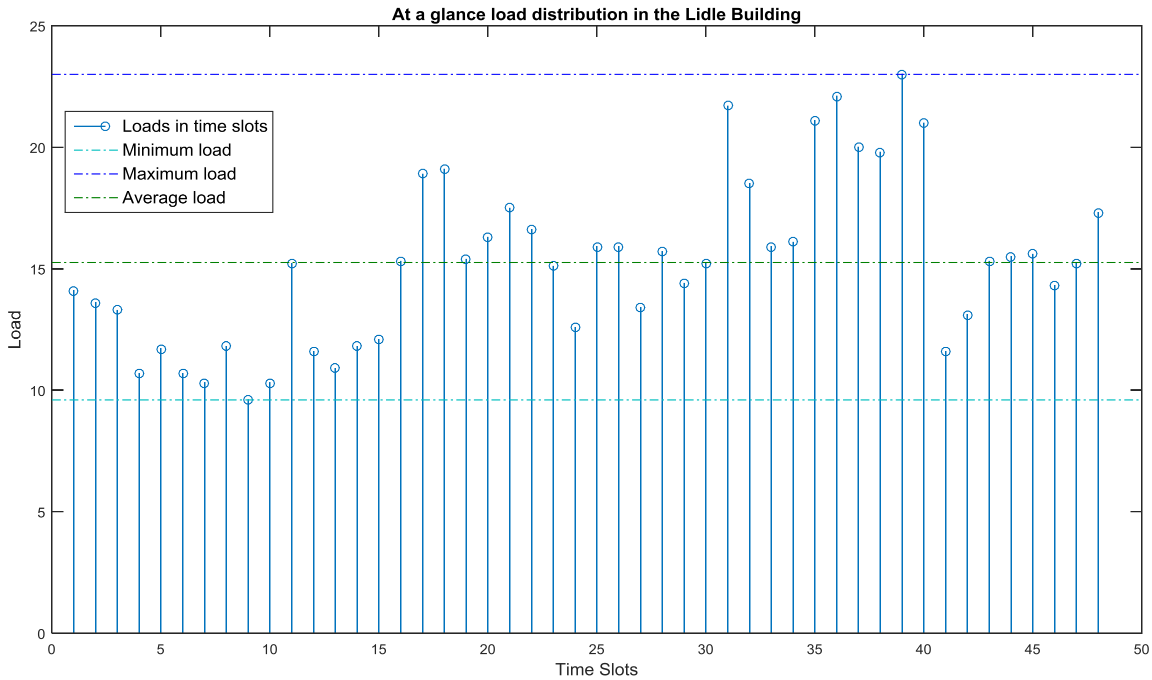


Figure 24: **Load distribution in the Lidle Building**

In the LRC building of the UoB (figure 35), the lowest consumption measured is 114.8 kWh, the maximum load measured is 251.2 kWh and peak load measured is 178.4 kWh. Load in different time slots follow a normal distribution.

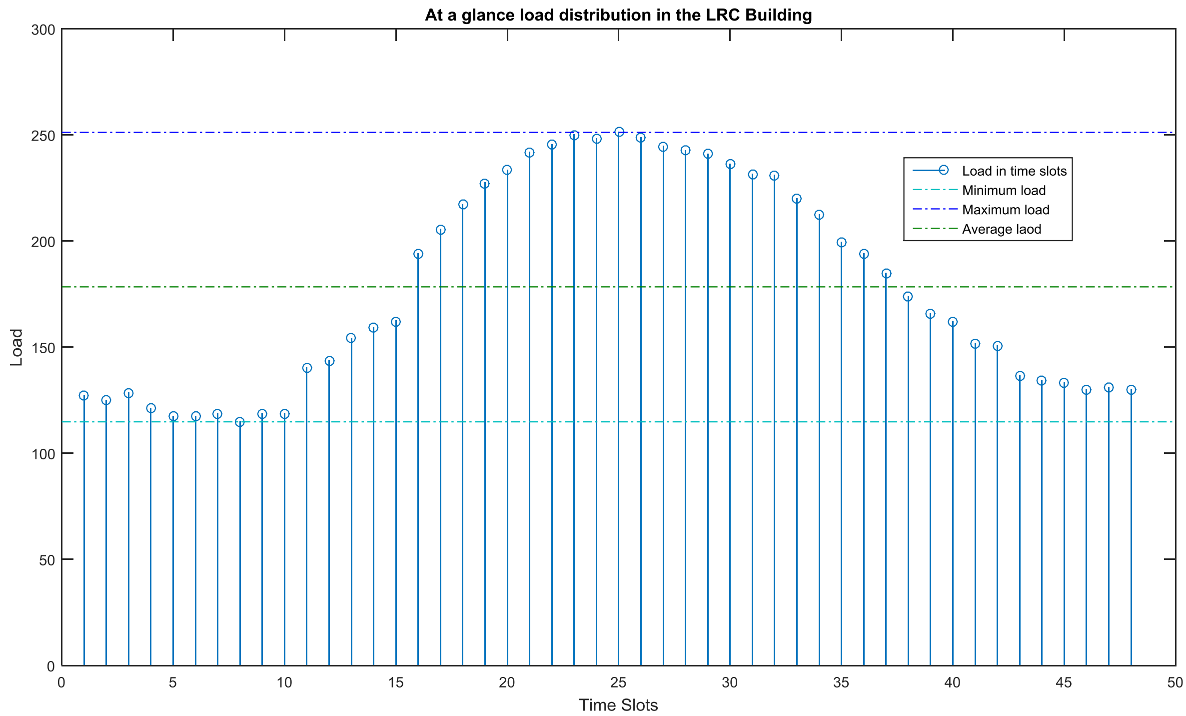


Figure 25: **Load distribution in the LRC Building**

In the Paget building of the UoB (figure 36), the lowest consumption measured is 4.5 kWh, the maximum load measured is 16.2 kWh and peak load measured is 8.1 kWh. Load in different time slots do not follow a normal distribution, as well.

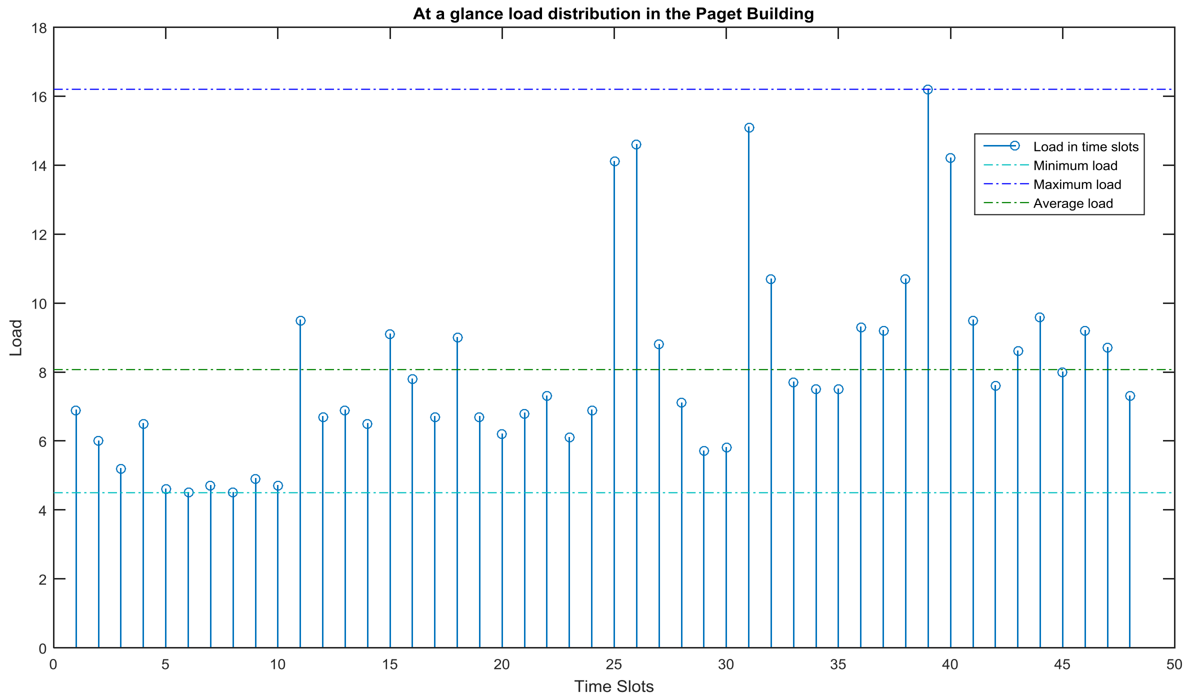


Figure 26: Load distribution in the Paget Building

In the Park Square building of the UoB (figure 37), the lowest consumption measured is 77.5 kWh, the maximum load measured is 92.3 kWh and peak load measured is 84.3 kWh. Load in different time slots do not follow a normal distribution, as well. This building uses almost similar energy consumption all day long.

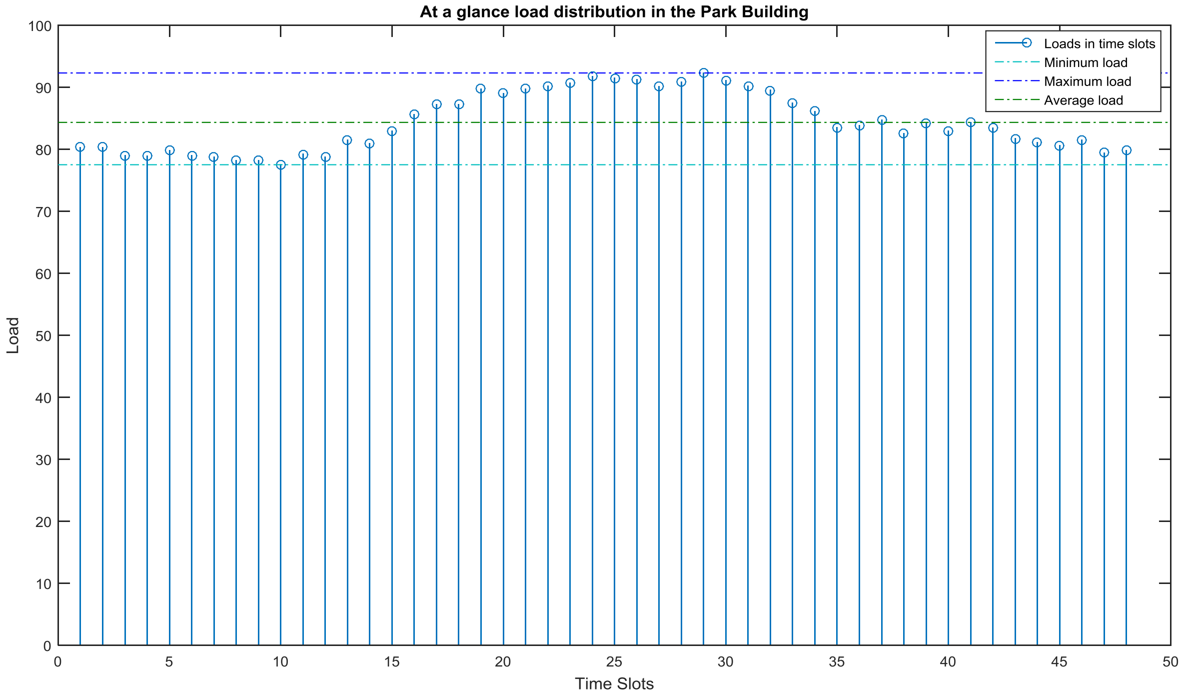


Figure 27: **Load distribution in the Park Square Building**

In the Scott building of the UoB (figure 38), the lowest consumption measured is 4.7 kWh, the maximum load measured is 11 kWh and peak load measured is 7.9 kWh. Load in different time slots do not follow a normal distribution, as well. This building uses dissimilar energy consumption all day long.

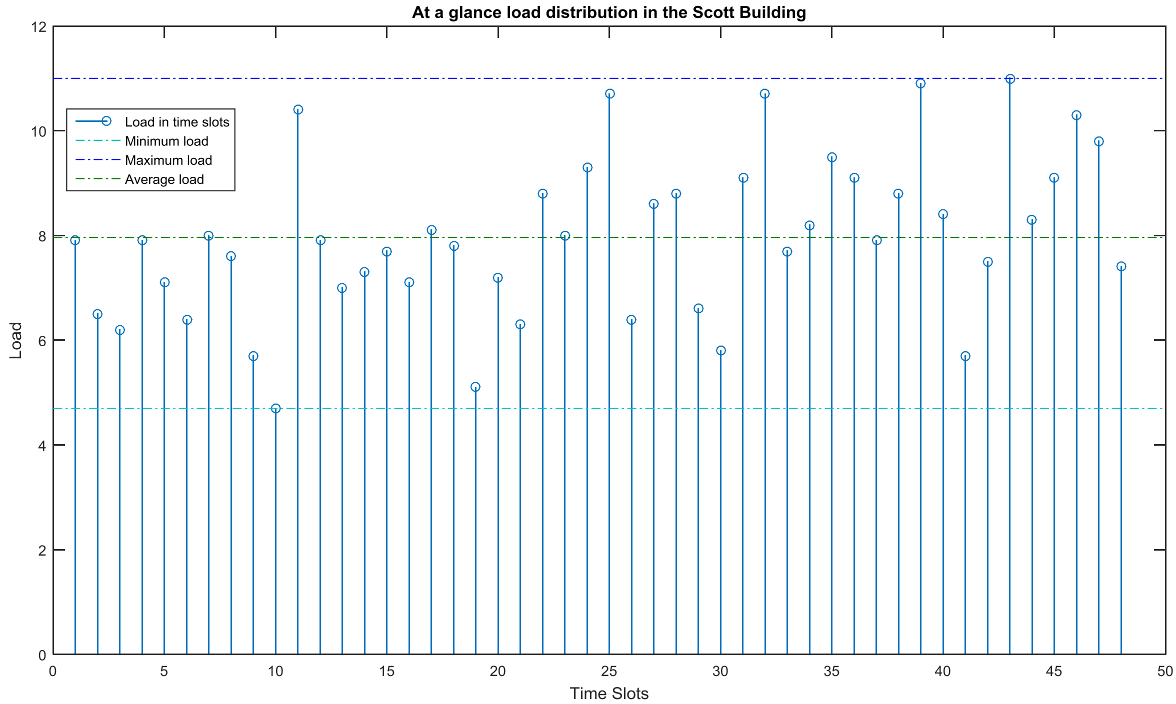


Figure 28: Load distribution in the Scott Building

In the Stephenson building of the UoB (figure 39), the lowest consumption measured is 6 kWh, the maximum load measured is 16 kWh and peak load measured is 9.1 kWh. Load in different time slots do not follow a normal distribution, as well. This building uses dissimilar energy consumption all day long.

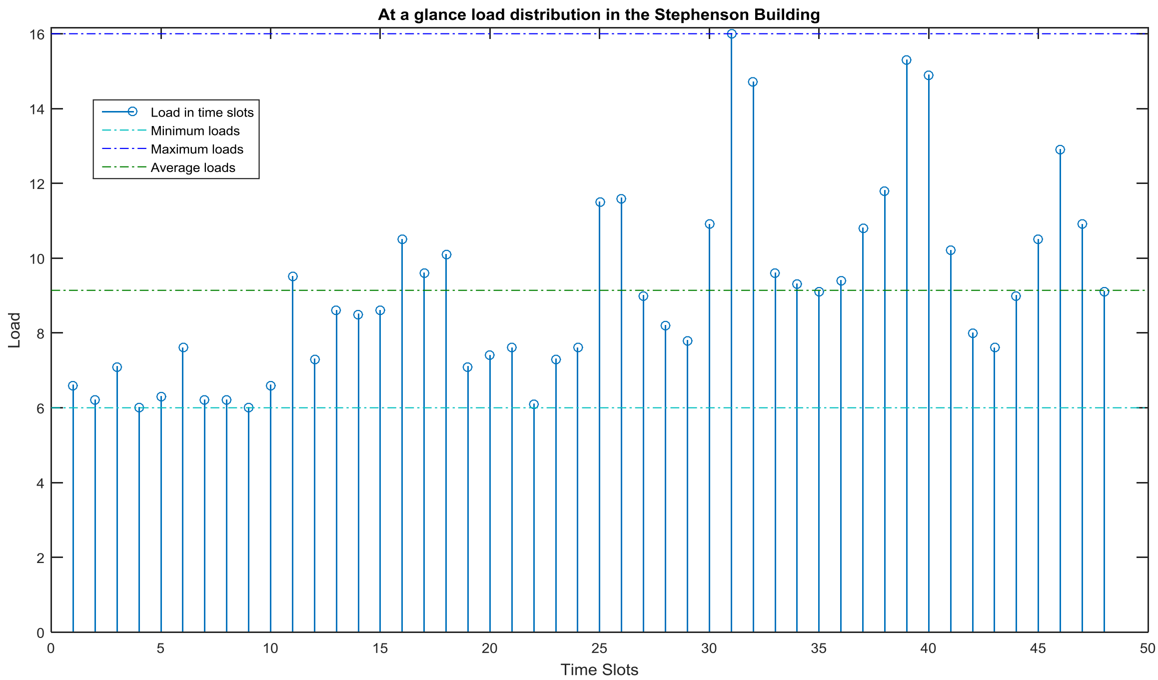


Figure 29: Load distribution in the Stephenson Building

In the Putteridge Bury building of the UoB (figure 40), the lowest consumption measured is 11.9 kWh, the maximum load measured is 49.5 kWh and peak load measured is 29.51 kWh. Load in different time slots do not follow a normal distribution, as well. This building uses dissimilar energy consumption all day long.

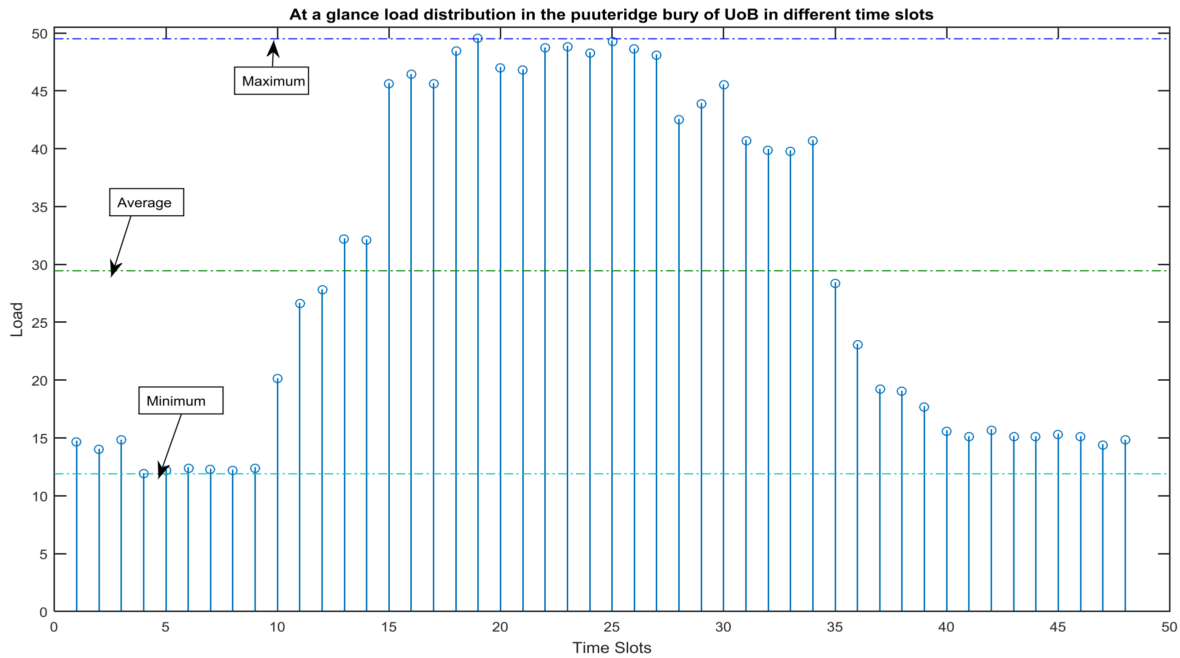


Figure 30: Load distribution in the Putteridge Bury Building

In the Stainiers building of the UoB (figure 41), the lowest consumption measured is 7 kWh, the maximum load measured is 16.1 kWh and peak load measured is 10.1 kWh. Load in different time slots do not follow a normal distribution, as well. This building uses dissimilar energy consumption all day long.

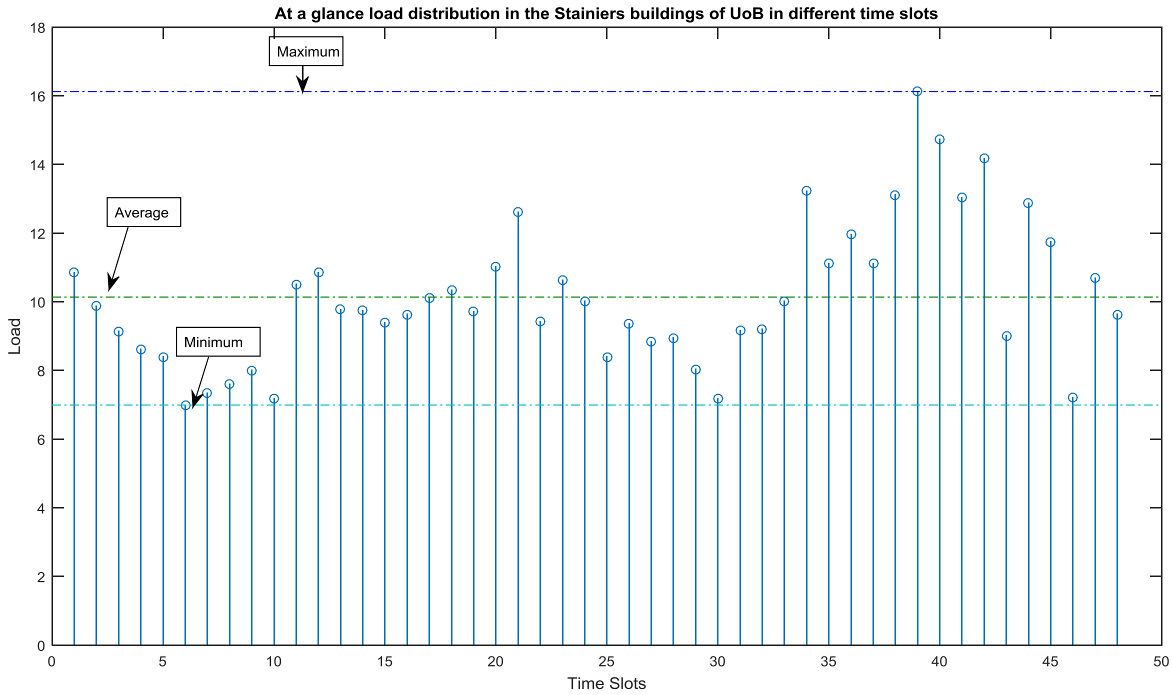


Figure 31: Load distribution in the Stainers Building

5.1.5 Overall total flat-rate pricing analysis in different buildings

We consider data collected from four DfE buildings. The TOU flat-rate price we have considered is one of the EP in the UK, Utility Warehouse. It charges a day base standing charge as well as a flat-rate unit price for the energy consumption throughout the day. The unit price of the EP is 13.84 pence. The graphical representations generated in MATLAB show their price distribution regarding price in pence per kWh. Figure 42 (Appendices) shows that the Sanctuary building is a large building, employees are using a variety of appliances from the first slot at 12 am to 11.30 pm, meaning that on a daily basis there is a total of 48 slots. St Pauls Place pays the medium price but the other two buildings, Castle View House and Mowden Hall, are comparatively small buildings and thus their bills are lower.

The volume of different buildings' energy usages is shown clearly in figure 43: that Sanctuary is a large building where electricity consumption is high. Castle View House and Mowden Hall are comparatively small buildings that have lower consumption and price, but St Pauls Place is a medium-size building where the medium level of price has been charged. Regarding buildings, a total of 283,480 pence for the Sanctuary building has been charged. The total price for Castle View House is 17,892 pence, the total price for Mowden Hall is 54,097 pence, and the total price for St Pauls Place is 95,765 pence.

This graphical representation in figure 43 (Appendices) shows that the Sanctuary building has significant costs associated with energy usage, St Pauls Place has lower, but still substantial costs, and Mowden Hall and Castle View House are small and have much lower costs. Therefore, all can benefit from reduced costs, but the larger buildings should receive priority in the algorithm being developed. Our algorithm successfully manages to reduce users' bills through the use of a Price Control Unit and Price Suggestion Unit (PSU) which work together to reduce user bills and the peak load for energy providers.

Regarding energy consumption, the graphical representation in figure 44 (Appendices) shows that energy usage is high from 8 am to 8 pm, mostly at lunchtime. Flat-rate pricing patterns follow the load patterns of the four buildings. Total demand based on four buildings is 32,588 kWh. However, average user demand per time slot is 678.9 kWh where peak demand is 1073.5 kWh and minimum demand is 322.3 kWh. Based on demand, flat-rate pricing has been applied, adding to the standing charge. As our data has been collected from two different organisations, DfE and UoB, we have analysed each organisation, as well as individual building based and obviously, from the EP's point of view. The graphical representation in figure 44 shows how UoB buildings have been charged by flat rate including per day standing charge.

The graphical representation in figure 45 shows overall flat-rate pricing distribution in different time slots. The total flat-rate pricing for the 14 different buildings shows that every building is being charged based on their consumption. However, they are being charged on a flat-rate basis. The flat-rate pricing does not treat the energy users fairly because the standing charge for every type of the customers is the same. Sometimes, the EP cannot collect the energy consumption from the energy users regularly as energy users do not want to provide their meter readings on a regular basis because it is time-consuming for them. Therefore, the EP produces an estimated bill for energy users as the whole system is a uni-directional communication. If the EP fails to collect a meter reading from the users on a monthly basis, then they have to adjust the load in the month of receiving the actual meter reading. Ironically, the cost of the users may be high or low to adjust the bill. The EP charges the energy users if energy users have high usages. The graph in figure 45 explains the flat-rate bill charged to the energy users from the EP perspective.

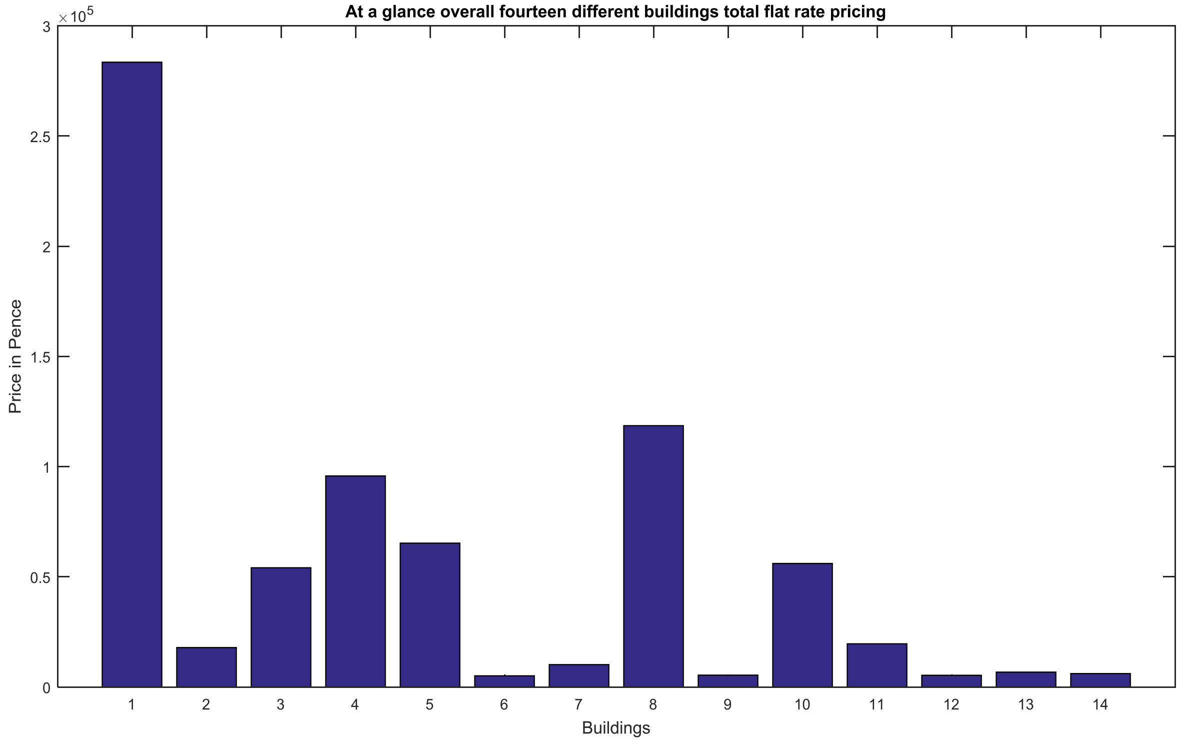


Figure 32: **Total flat-rate price paid in all 14 different buildings**

The graphical representation (figure 46) shows the flat-rate total price charged in the different time slots. This figure is concise with different coloured timeslots. At a glance, it shows where the charge is high or low in real time basis. Buildings are charged and vary in different time slots. However, we have shown how real-time price is implemented in terms of price selection in section 5.1.12. Time slot based pricing is important to understand real-time pricing. We will discuss this in detail in section 5.1.13.

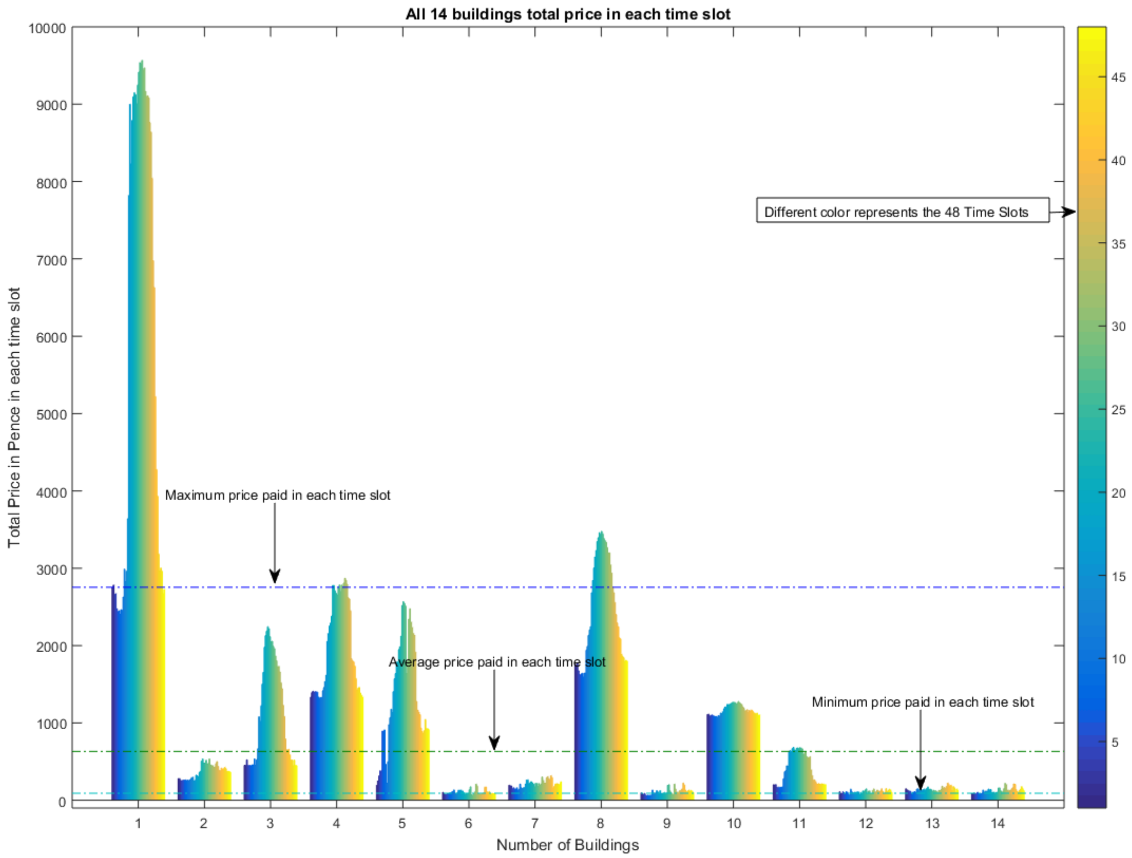


Figure 33: Total price paid by in different time slots for all 14 buildings

5.1.6 Individual building based flat-rate pricing

In this section, we have analysed building based TOU or flat rate price charged in different time slots. It has been thoroughly analysed and put most of the figure in the appendices. However, some of the sample figures have been kept in this section to understand how every building is differently charged.

In the Sanctuary building, the graphical representation in figure 47 (Appendices) shows that the flat-rate price charged in different slots is based on load consumption. However, RT pricing varies in different slots, which we will show in section 5.1.13. They mostly use their energy from 7.30 am to 4 pm. The spike in time slot number 17 means 8 am shows users use energy a bit more than at other times and accordingly, it has been charged. It may be because employees turn up in the morning at the office to have a cup of tea or coffee, using a kettle which consumes a lot of energy.

In figure 48 (Appendices), Castle View House usage is mostly 10.30 am to 5.30 pm. RT pricing fluctuates which is shown in the next section 5.1.12, but the flat-rate price shows they are charged by their energy consumption pattern. Time slot numbers 22, 23, 26, 29 means 10.30 am, 11 am, 12.30 pm and 2.00 pm are highly charged as employees used energy in that period highly. However, it has been charged mostly all the way from the beginning to end in a whole day 24-hour period.

In Mowden Hall, we have mentioned in the later stage in the section 5.1.13 that its PAR is high. The graphical representation in figure 49 (Appendices) shows that the flat-rate price imposed is based on their usage pattern. They have very high consumption from 9 am to 11 am, which conferred an unbalanced load. However, RT pricing and PSU suggestion would help them to reduce their load so that they would be better off. Time slot numbers 20–23 means 9.30 am to 11.00 am are charged highly as they used energy highly.

In figure 50 (Appendices), St Pauls Place has a high load from 10 am to 4.30 pm. Flat rate is not the solution for them; RT pricing significantly reduced their price and PSU would allow them to reduce the bill more. The SPSA algorithm assists in reducing their bill. Time slot numbers 21, 22, 33, 34 means 10–11 am, and 4–5 pm were charged heavily because usages were high.

In the Campus building of UoB (in figure 51), time slot numbers 24–27, 31 means 11.30 am to 1.30 pm and 3 pm were the highest usage periods. At 4.30 am was the lowest usage. Flat rate is being charged based on the load consumed. This building is not following a pattern as normal as other buildings in the same institution, rather it is jerky as there is no pattern it follows. Flat-rate price is implemented straight. However, RT price would be the better solution for them.

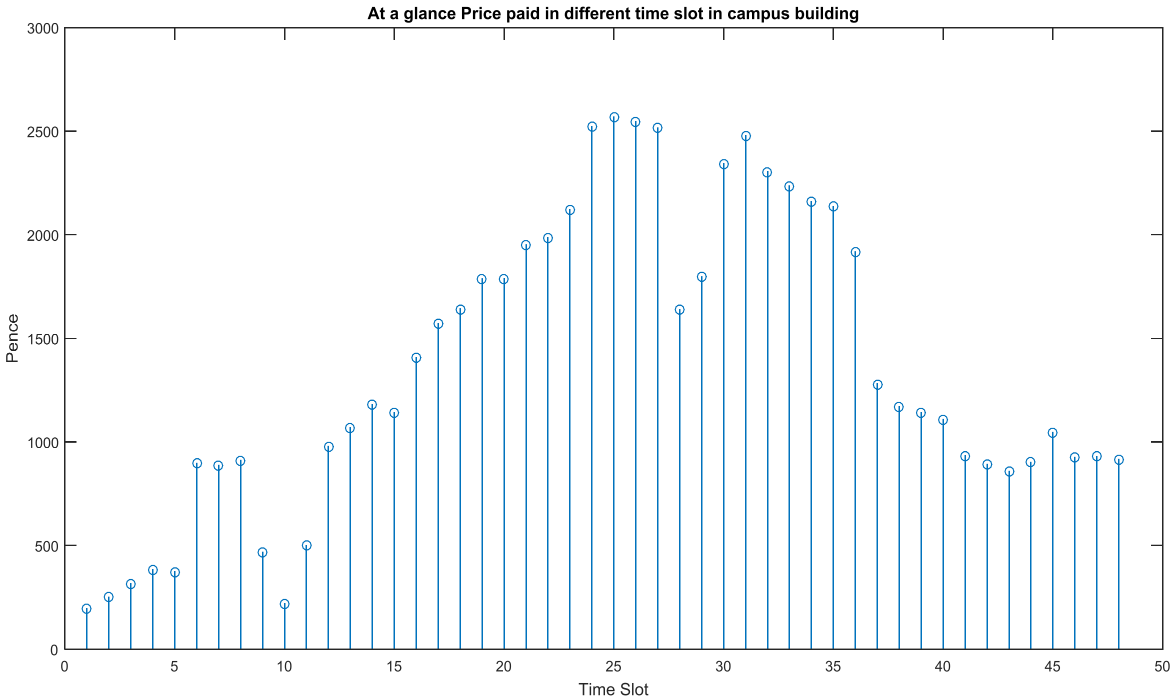


Figure 34: **Price paid in different time slots in the Campus building**

In the Johnson building of UoB (in figure 52), time slot numbers 26, 31, 39, 40 means 12.30 pm, 3 pm, 7–8 pm were the highest usages. At 1.30 pm was the lowest usage. Flat rate is being charged based on the load consumed. This building is rather bumpier than others as this is not following any pattern. Sometimes user consumption is very high and sometimes very low. Flat-rate price implemented straight, but RT price is also the better solution for them. Similarly, in the Paget building of UoB (in the Appendices, figure 55), time slot numbers 25, 26, 31, 39 means 12–1 pm, 3 pm and 7 pm were the highest usages. At 2.30 am was the lowest usage. Similarly, in the Scott building of UoB (in the Appendices, figure 60), they have time slot numbers 11, 25, 32, 39 means 5 am, 12 pm, 3.30 pm and 7 pm were the highest usages. At 4.30 am was the lowest usage.

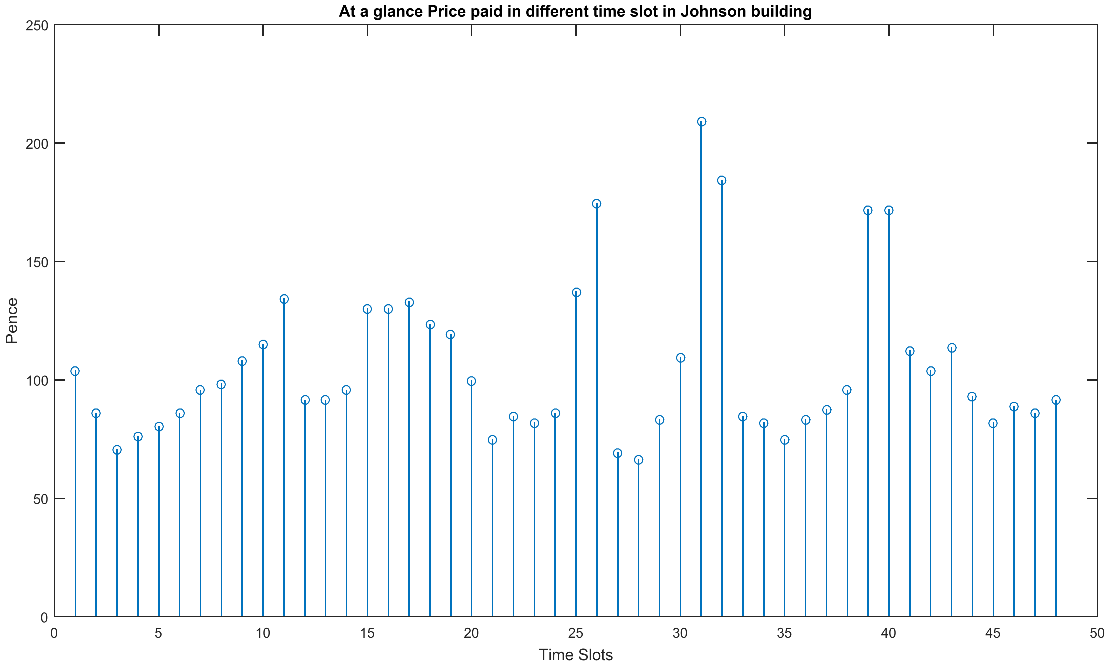


Figure 35: **Price paid in different time slots in the Johnson building**

In the Lidle building of UoB (in the Appendices, figure 53), time slot numbers 31, 36, 39 means 3 pm, 5.30 pm, 7 pm were the highest usages. At 4 am was the lowest usage. Flat rate is being charged based on the load consumed. This building's load almost follows almost similar consumption over the whole period of 24-hour time but some of the time their usages spike and it does not follow any pattern. Flat-rate price implemented straight through is based on their consumption.

In the LRC building of UoB (in figure 54), time slot numbers 20–30 means 9.30 am to 2.30 pm, were the highest usages. At 3.30 am was the lowest usage. Flat rate is being charged based on the load consumed. This building looks to follows the bell-shaped loads and price. Flat-rate price is implemented based on their total usages. Similarly, in the Putteridge Bury building of UoB (in the Appendices, figure 57), they have time slot numbers 19 and 25 means 9 am, 12 pm, were the highest usages. At 1.30 am to 4 am was the lowest usage. Price consumption follows 7 am to 16.30 am almost higher than at other times.

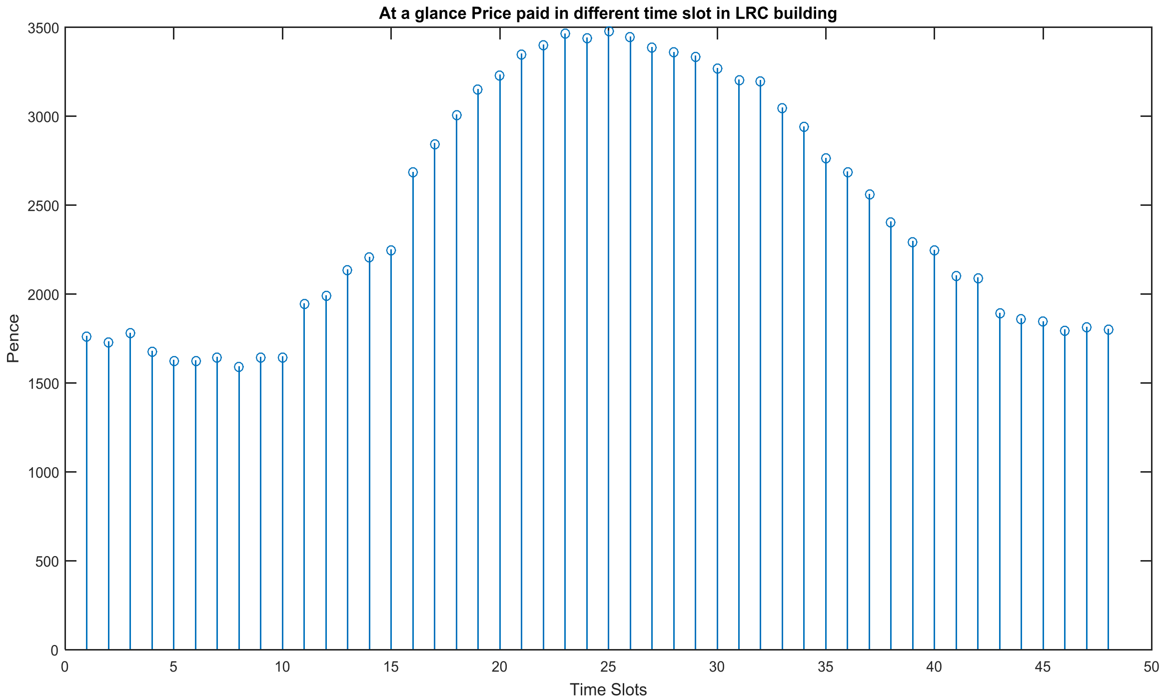


Figure 36: **Price paid in different time slots in the LRC building**

In the Park Square building of UoB (in figure 56), time slot numbers 24, 29 means 11.30 am, 2 pm, were the highest usages. At 5.30 am was the lowest usage. Flat rate is being charged based on the load consumed. Users are consuming energy almost all day with a similar pattern of usages. Flat-rate price is implemented by their consumption. This is exceptionally followed almost similar usages in different time slots.

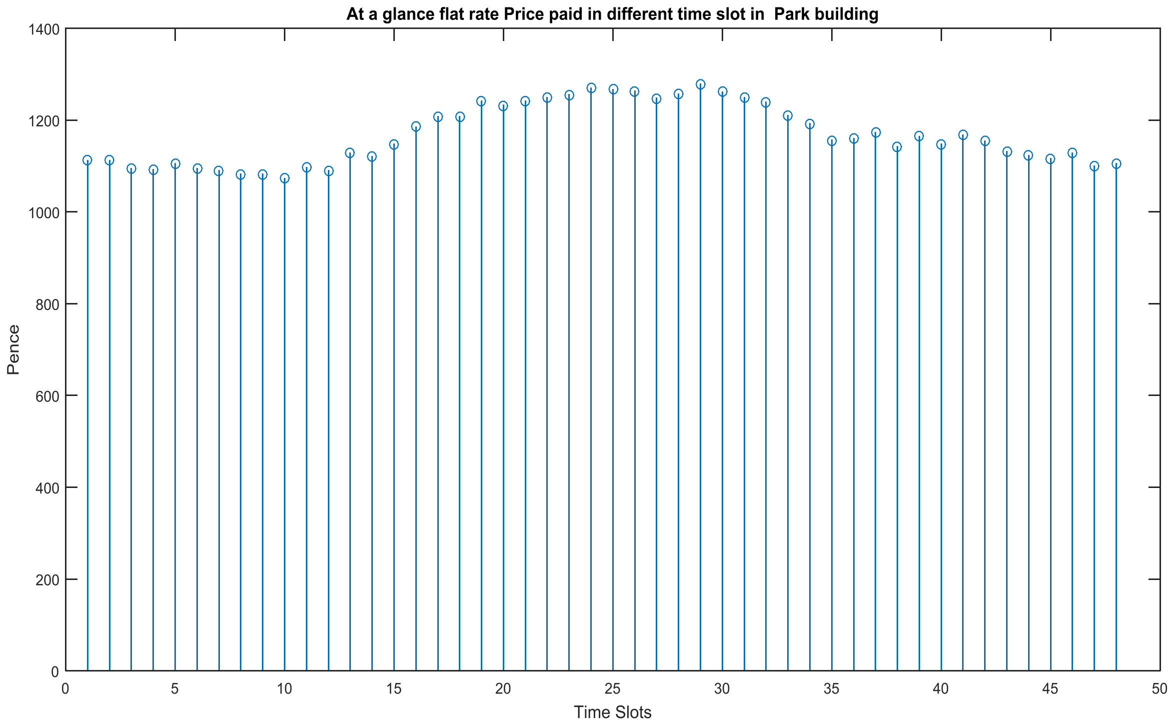


Figure 37: **Flat-rate price paid in different time slots in the Park Square building**

In the Steiniers building of UoB (in figure 59), time slot number 39 means 7 pm was the highest usage. At 2.30 pm was the lowest usage. Flat rate is being charged based on the load consumed. Energy consumption is almost similar, except some of the slots used more. Flat-rate price is implemented by their consumption. Similarly, in the Stephenson building of UoB (in the Appendices, figure 58), they have time slot numbers 31 and 39 means 3 pm, 7 pm, were the highest usages. At 10.30 am was the lowest usage.

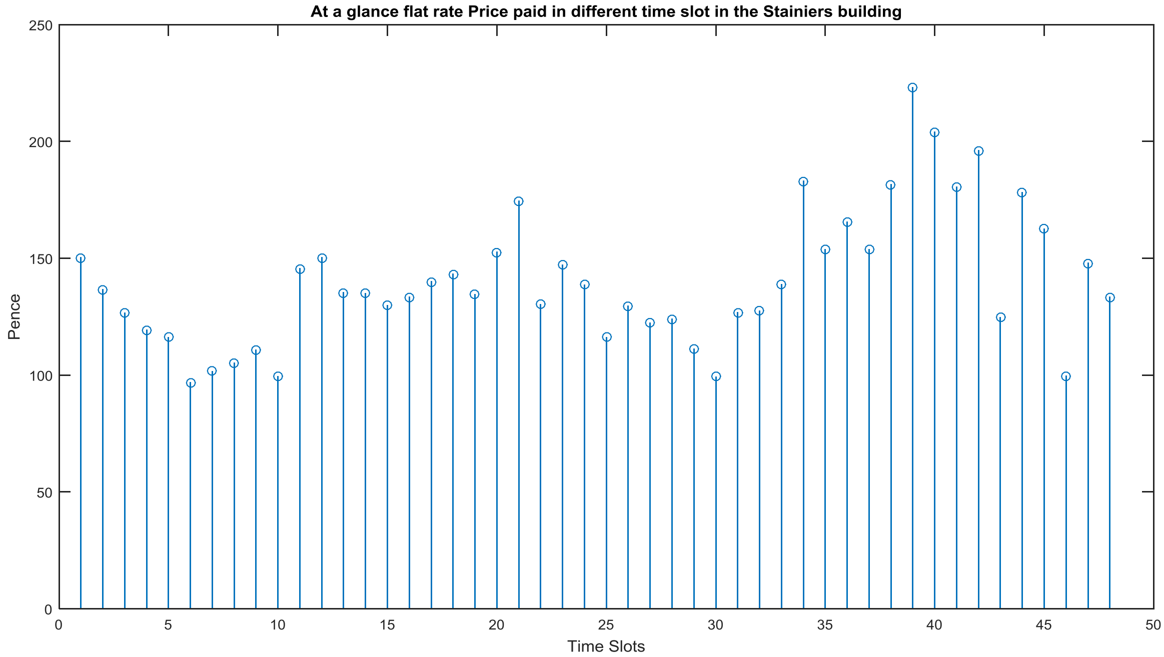


Figure 38: Flat-rate price paid in different time slots in the Stainers building

5.1.7 Real-Time (RT) Price selection in different buildings

Real-Time pricing should be dynamic. An Energy Provider's decision on price selection may impact the user profile because energy unit price will be introduced by the EP. The EP can set their unit price based on the marginal cost of their energy buying price from the power transmission. Then this unit price would be calculated as maximum and minimum based on the threshold load on the user profile. We have used the same unit price for TOU flat rate and real-time pricing for our experiment. Our algorithm uses a dynamic charge, either pricing maximum or minimum on the user profile on a half-hourly basis. We have explained this in section 4.5.2 in equation 2. The graphical representations show how those minimum and maximum usages are based on the threshold load in different buildings. We have analysed for all 14 buildings. However, we kept most of the analysis in the appendices and some of them kept in the main thesis to understand real-time dynamic charging on different buildings.

Overall pricing is also implied in the price parameter, but because of data variability, the price implied in the individual building has obtained a significant result. Real-Time pricing benefits the buildings. The graphical representation in figure 61 shows how the Sanctuary building is being charged low and high prices.

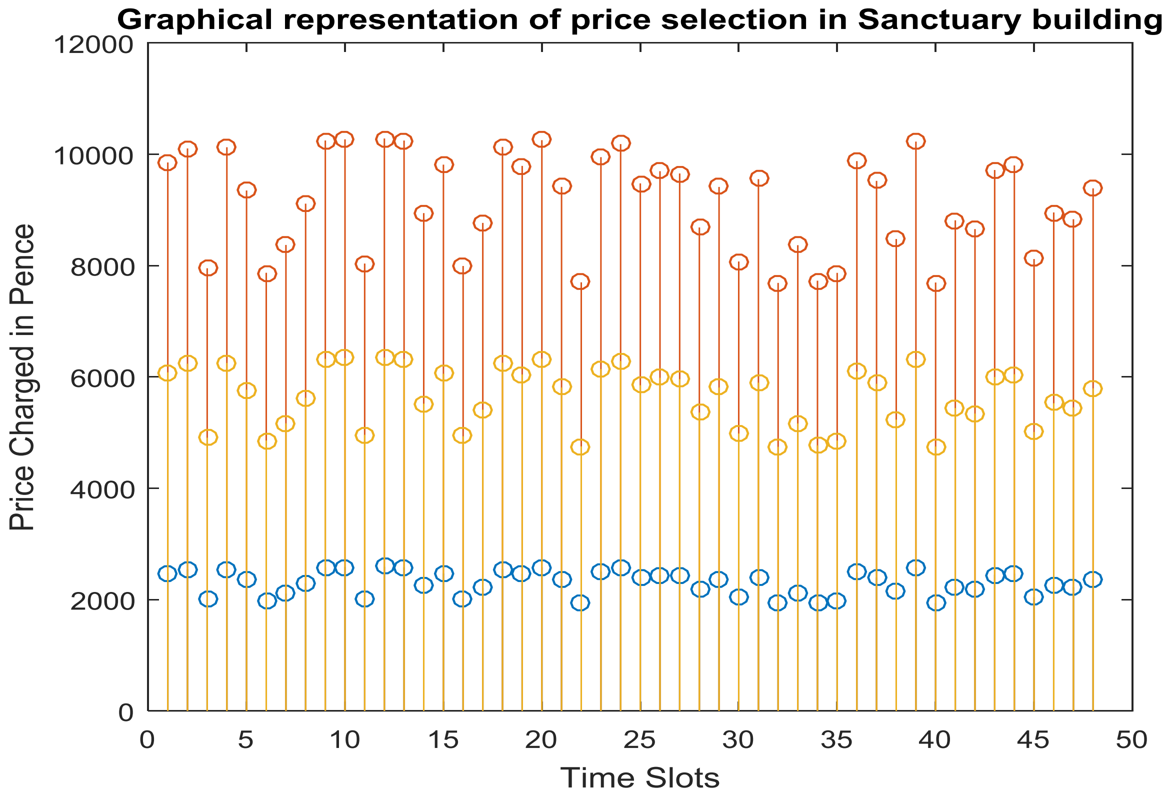


Figure 39: **Max, min charged in Sanctuary Building for RT price calculation**

The graphical representation in figure 62, 63, 64 (Appendices) shows how these buildings are being charged low, average and high prices. Real-Time (RT) Price charged in different time slots is based on consumption. If the user uses more than the threshold they would be charged the higher rate, otherwise the lower rate.

The graphical representation in figure 65 show how this building was charged in different time slots; RT price selection was on a real-time basis, points blue, yellow and red were the low, threshold and high prices. The Stephenson building of UoB time slots is charged almost on the threshold basis because of its similar type of energy usage pattern. This building may save a lot regarding flat-rate pricing which we will discuss at a later stage.

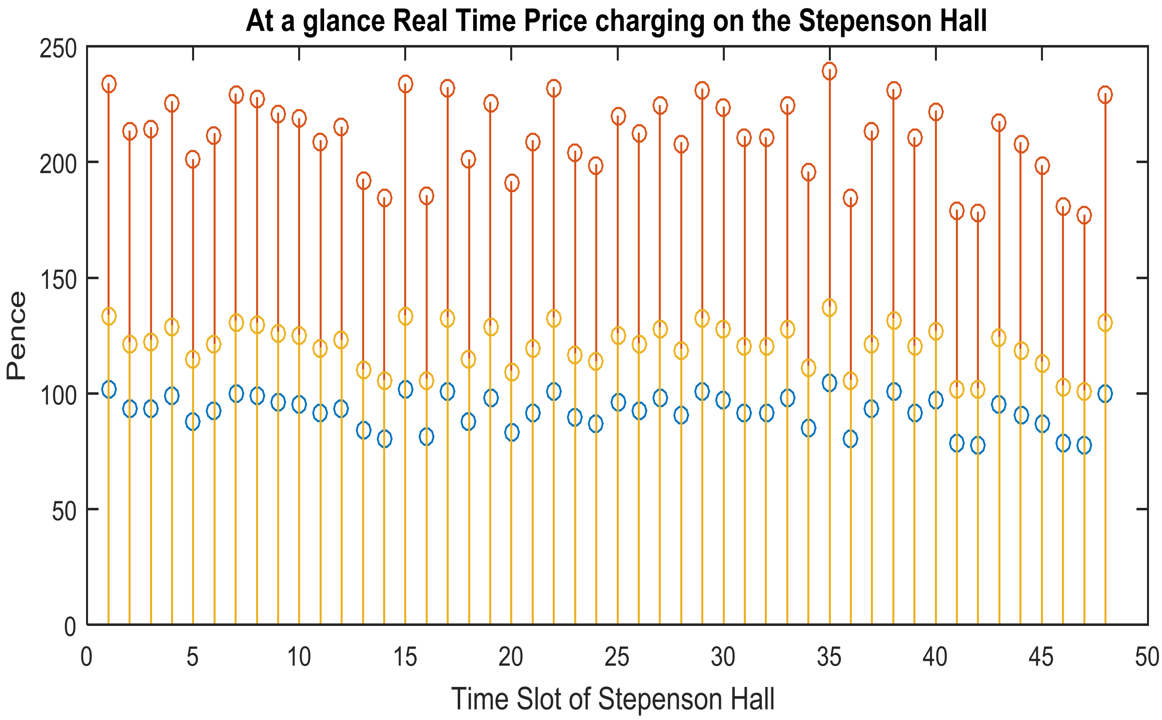


Figure 40: **Maximum, minimum charges in Stephen Hall for real-time price calculation**

Similarly, the graphical representation in figure 66, 67 (Appendices) show how Stainers building was charged in different time slots; it consumed on an almost similar pattern of energy consumption, so it would save on its bill in terms of a flat rate. We will discuss how it has saved on its bill by implementing the RT price.

The graphical representation in figure 68 shows how Putteridge Bury building was charged in different time slots; the RT price selection was on a real-time basis, as we can see every point blue, yellow and red were the low, threshold and high prices. It consumed almost on a steady level of energy consumption, so it would save on its bill in terms of a flat rate. We will discuss how it has saved on its bill by implementing the RT price. Most of the minimum charge was a similar pattern.

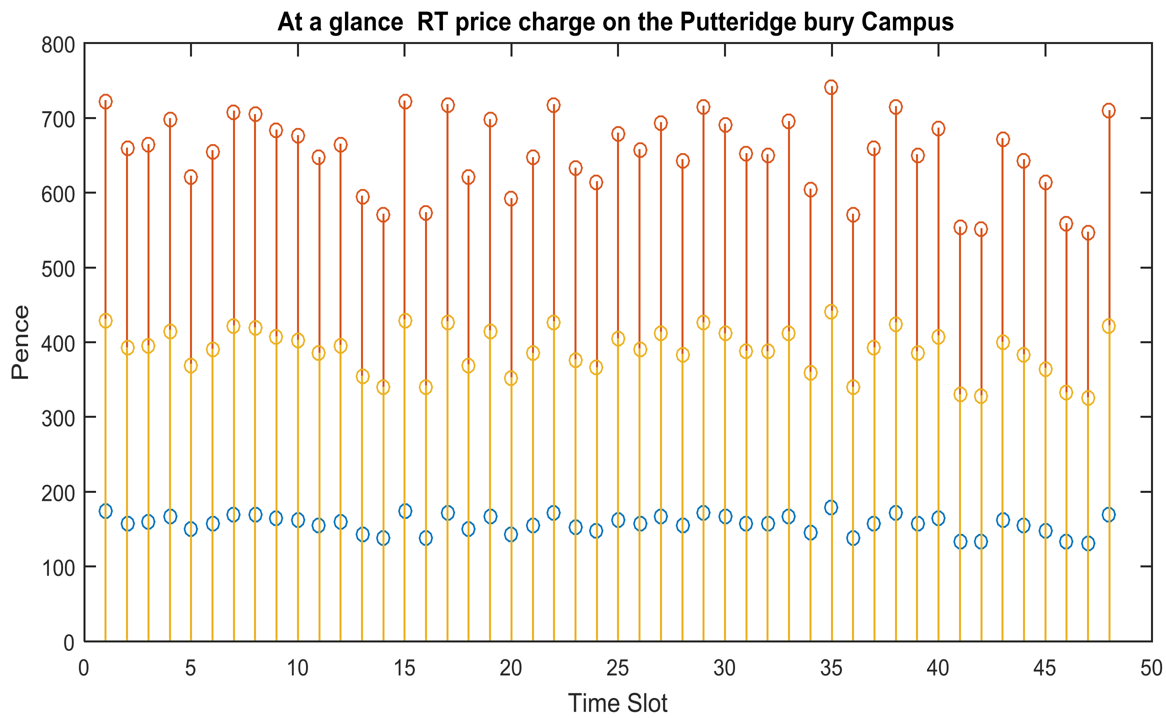


Figure 41: **Max, min charges in Putteridge Bury for real-time price calculation**

Graphical representations in the figure 69 shows how Park Square building was charged in different time slots; the RT price selection was on a real-time basis, every point blue, yellow and red were the low, threshold and high prices. It consumed almost on an upper-level pattern of energy consumption, so it would save on its bill in terms of a flat rate. We will discuss how it has saved on its bill by implementing the RT price. This building's price was always high as per graph shows, even the lowest price was high because of the pattern of their consumption.

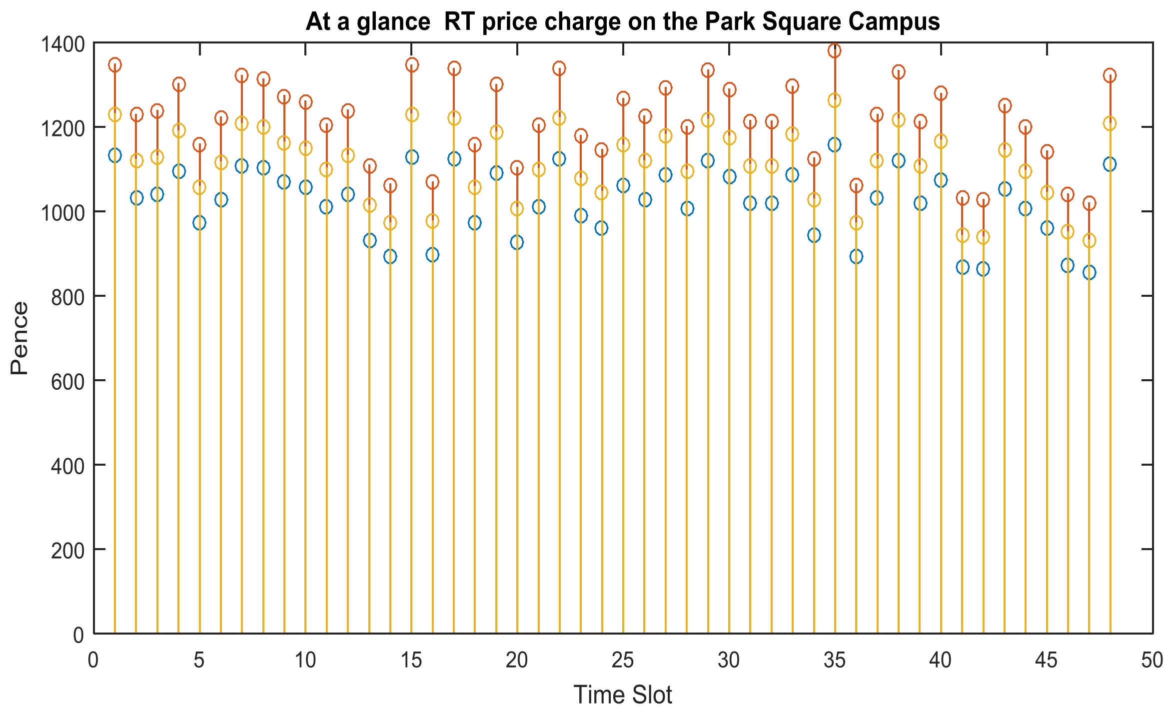


Figure 42: **Maximum, minimum charges in Park Square for real-time price calculation**

Graphical representations in figure 70, 71 (Appendices) show how this building was charged in different time slots; the RT price selection was on a real-time basis, every point blue, yellow and red were the low, threshold and high prices. Paget building consumed on an almost bumpy pattern of energy consumption. However, it would save on its bill in terms of a flat rate. We will discuss how it has saved on its bill by implementing the RT price.

Graphical representations (figure 72) show how this building was charged in different time slots; The RT price selection was on a real-time basis, every point blue, yellow and red were the low, threshold and high prices. The Johnson building consumed almost similar pattern of energy consumption so it would save on its bill in terms of a flat rate. We will discuss how it has saved on its bill by implementing the RT price.

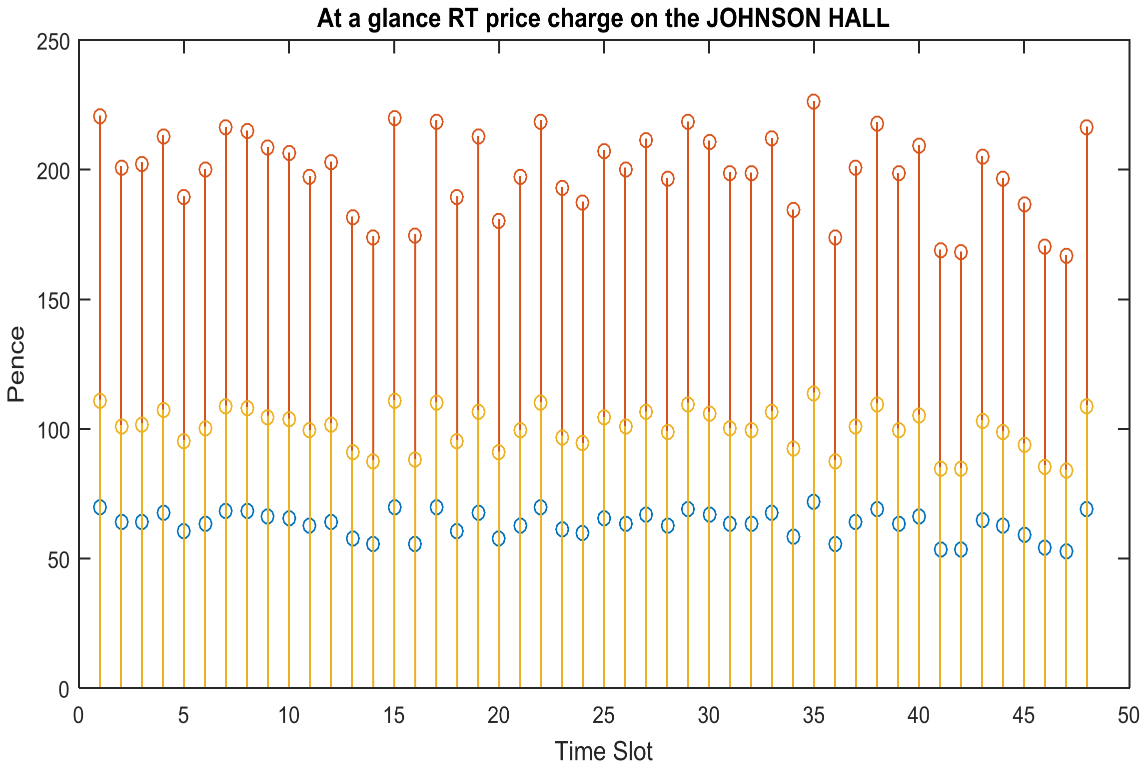


Figure 43: **Maximum, minimum charges in Johnson hall for real-time price calculation**

The graphical representation in figure 73 shows how this building was charged in different time slots; The RT price selection was on a real-time basis, every point blue, yellow and red were the low, threshold and high prices. The Campus building consumed almost similar pattern of energy consumption so it would save on its bill in terms of a flat rate. We will discuss how it has saved on its bill by implementing the RT price. This building has been charged lowest in case of minimum consumption.

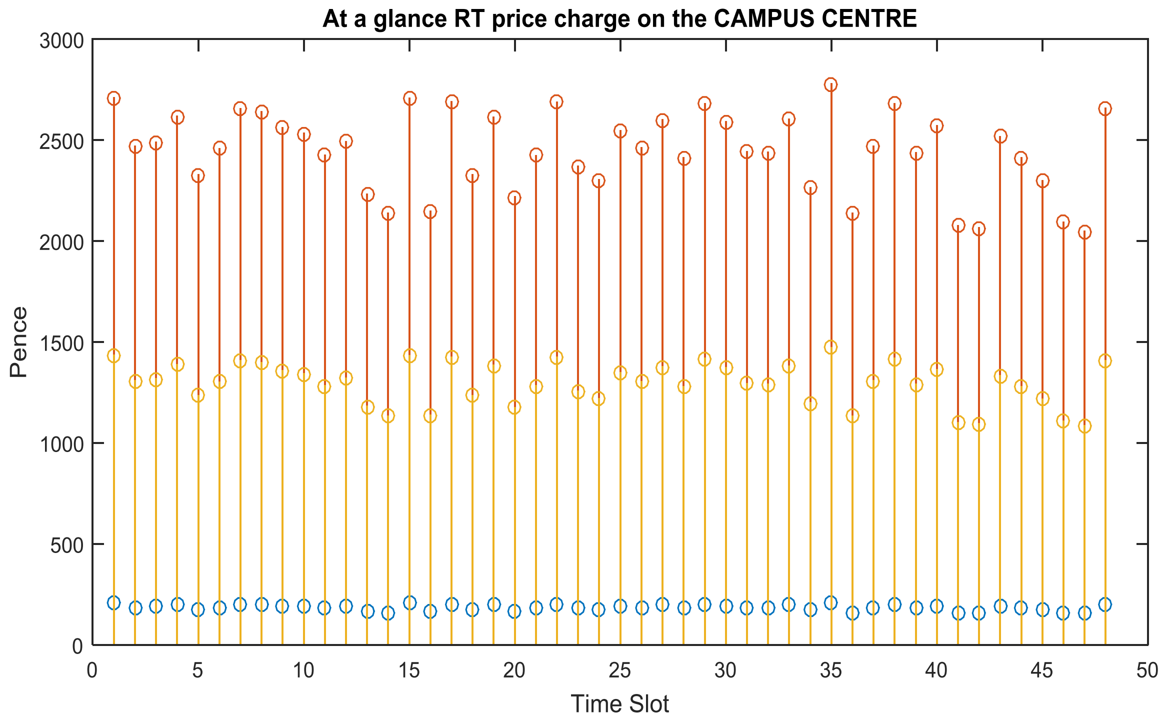


Figure 44: Maximum, minimum charges in Campus Centre for RT price calculation

Graphical representations in figure 74 (Appendices) show how this building was charged in different time slots; The RT price selection was on a real-time basis, every point blue, yellow and red were the low, threshold and high prices. The Lidle building consumed almost similar pattern of energy consumption so it would save on its bill in terms of a flat rate. We will discuss how it has saved on its bill by implementing the RT price.

5.1.8 Real-Time price distribution in different buildings without considering load shifting

To determine the best price practice, real-time basis generation and distribution costs should be exposed to pricing. Vibrant real-time pricing benefits the SG. In the scenario of deployment of the SG, customers would be in communication through a smart meter. It provides benefits within the UK by reducing electricity usage by 3%, and peak demand by 5% [17]. The EP demand response programme itself assists in reducing by one-sixth of the total benefits in the deployment of SG even with flat-rate pricing. In the flat-rate pricing model, some of the users might be overcharged or undercharged while they are responding on a Time-of-Use (TOU) basis (flat-rate pricing) on incentives. However, real-time pricing is the solution for them as there will be no question of over- or undercharging for their usage as our model shows how real-time pricing reduced their bill significantly in terms of flat-rate price. Real-time pricing is based on generation, transmission and distribution costs. The bi-directional SG with a smart meter will be used in the real-time pricing. Hence, our model accommodated the smart meter. This section provides the overview of how the buildings are charged without load shifting.

In figure 75 (Appendices) for Sanctuary building, time slots like 7.30 am, 10 am, 10.30 am, 1 pm, 3.30 pm and 7.30 pm are charged, highly, and we could suggest that if they can shift their load from those slots to suggested time that would reduce their bill significantly. Castle View House in figure 76 (Appendices) was highly charged particularly at 11.30 am 12.30 pm, 3.30 pm, 4.30 pm, 8.30 pm and 9.30 pm because of their over-usages. This building is a relatively small building where excessive use may have an impact on their real-time price. However, overall they are better off with RT price not with flat-rate pricing. Similarly, in figure 77 (Appendices) for Mowden Hall, they have over-usages from 7.30 am to 5.30 pm with a similar pattern. The 4.30 pm time slot is highly charged. Their Peak-to-Average (PAR) load is 4% and disproportionate, they have to shift their load in the lower usage area. RT pricing and flat-rate pricing have the same impact on them. In RT pricing, they have lost very insignificantly 0.006%. Price Suggestion Unit (PSU) would suggest them to shift their load to lower usage area so that they would better off in reducing their bill. In figure 78 (Appendices) St Pauls Place is charged higher at 7.30 am, 10.00 am, 10.30 am, 3.30 pm. However, they are better off with the RT pricing system then flat-rate pricing. They have a better price in RT pricing. Still, PSU would suggest shifting their load in the particular slot where they have less usage. The conclusion is RT pricing is better than flat-rate pricing.

The graphical representation in figure 79 shows the time slot is being charged, some of them are charged a lower price as it has less than the threshold load consumed, some of them are charged high because users consumed energy higher than the threshold. For example, slot 11 means at 5 am is charged high, from our previous discussion of the Scott building load distribution, it was far more than the threshold. Similarly, slot number 17 means at 8 am is more than the threshold and charged high but the RT high price was less, it was charged less than the price at 5 am.

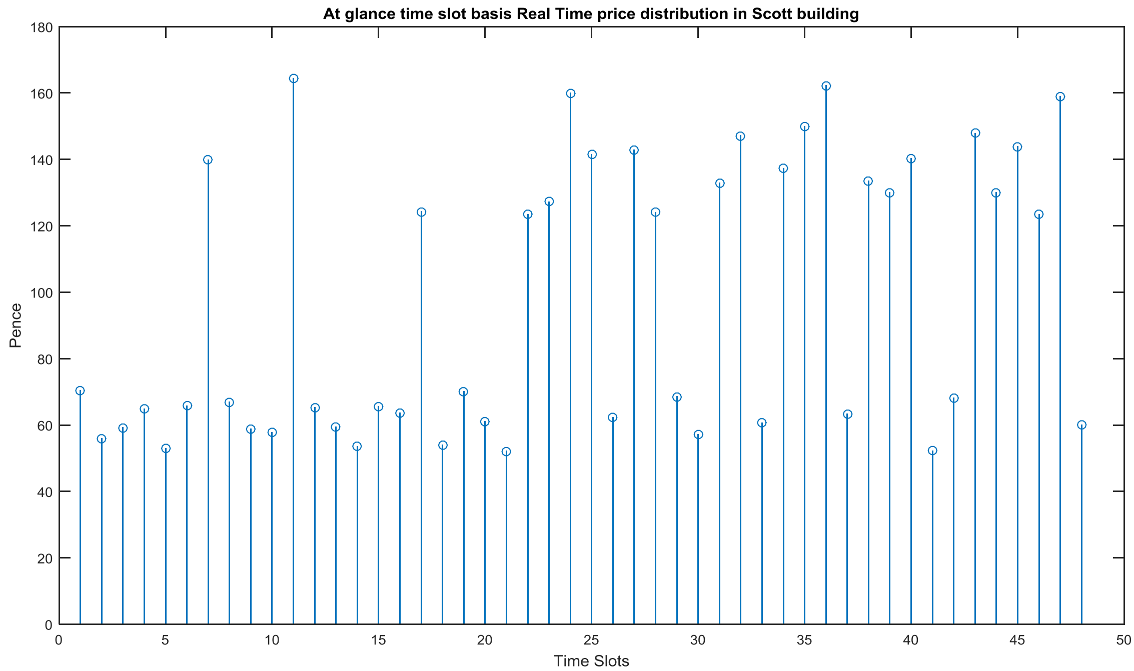


Figure 45: **Time slot basis real-time price distribution in the Scott building**

This graphical representation in figure 80 (Appendices) shows that how Stainers building is being charged on the RT basis in different time slots. Time slot number 1 means at 12 am to 12.30 am, in this particular half-hour the RT price charged is high, the reason being the load was more than the threshold and the RT price was high in that particular time, as well. Similarly, we see the same situation for 5–6 am, in the morning energy consumption was more than the threshold. Similarly, the Stephenson building RT price distribution is shown in figure 81 (Appendices).The RT price charged by load consumption on a real-time basis. Some of the time slots are highly charged. For example, time slot numbers 11, 36, 47 means 5 am, 5.30 pm, 11 pm, because they exceeded the threshold load and the RT price was high.

The Park Square building RT price distribution is shown in figure 82. The RT price is charged by load consumption on a real-time basis. Some of the time slots are highly charged. For example, time slot numbers 19, 24, 37 means 9 am, 11.30 pm, 6 pm, because they exceeded the threshold load and the RT price was high.

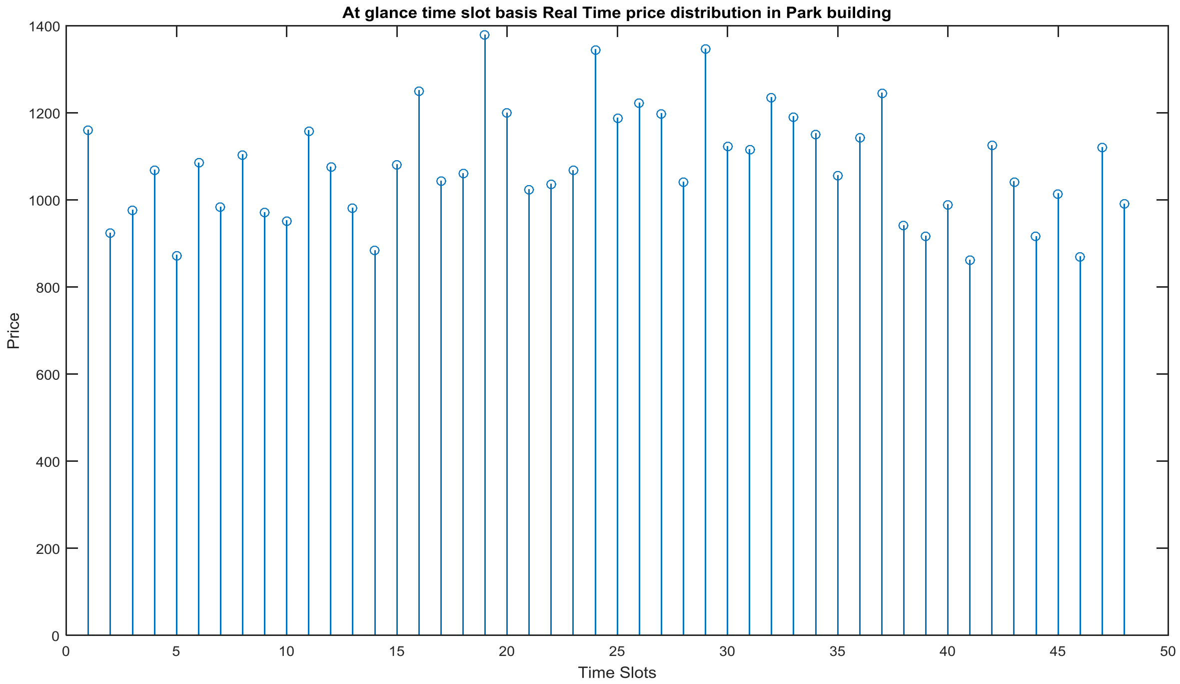


Figure 46: **Time slot basis real-time price distribution in the Park Square building**

The Paget building RT price distribution is shown in figure 83. The RT price is charged by load consumption on a real-time basis. Some of the time slots are highly charged. For example, time slot numbers 11, 15, 36, 47 means 5 am, 7 am, 5.30 pm, 11 pm, because they exceeded the threshold load and the RT price was high.

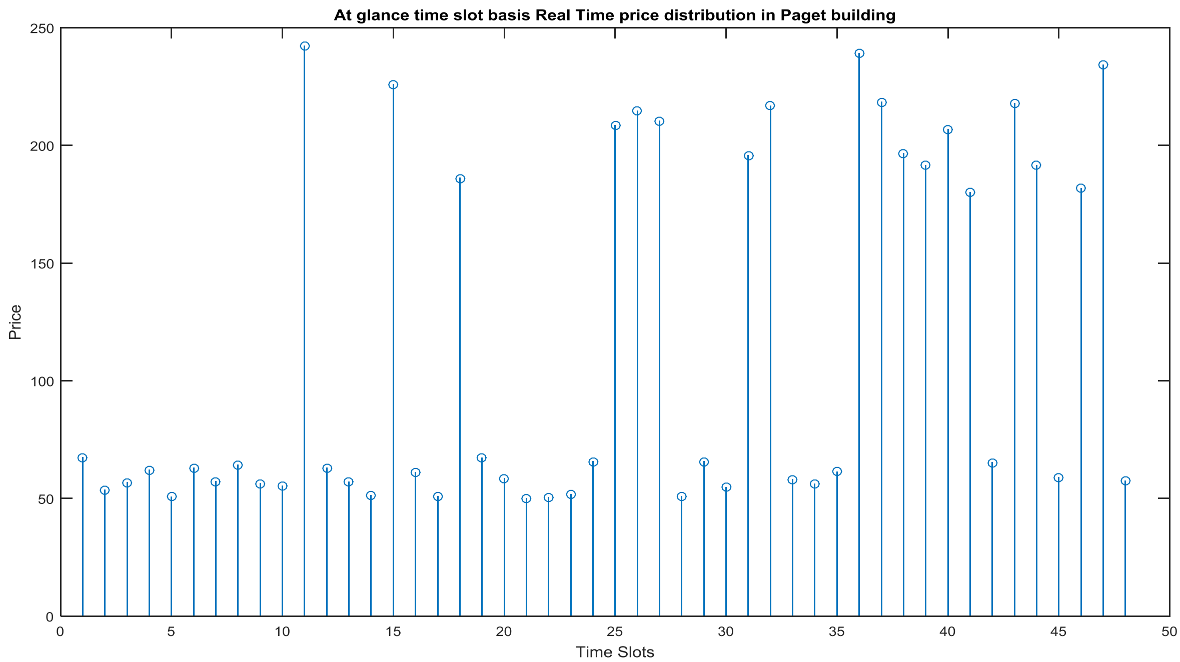


Figure 47: **Time slot basis real-time price distribution in the Paget building**

The LRC building RT price distribution is shown in figure 84 (Appendices). The RT price is charged by load consumption on a real-time basis. Some of the time slots are highly charged. For example, time slot numbers 16, 19, 24, 37 means 7.30 am, 9 am, 11.30 am, 6 pm, because they exceeded the threshold load and the RT price was high.

The Lidle building RT price distribution is shown in figure 85. The RT price is charged by load consumption on a real-time basis. Some of the time slots are highly charged. For example, time slot number 19, 36 means 9 am, 5.30 pm, because they exceeded the threshold load and the RT price was high.

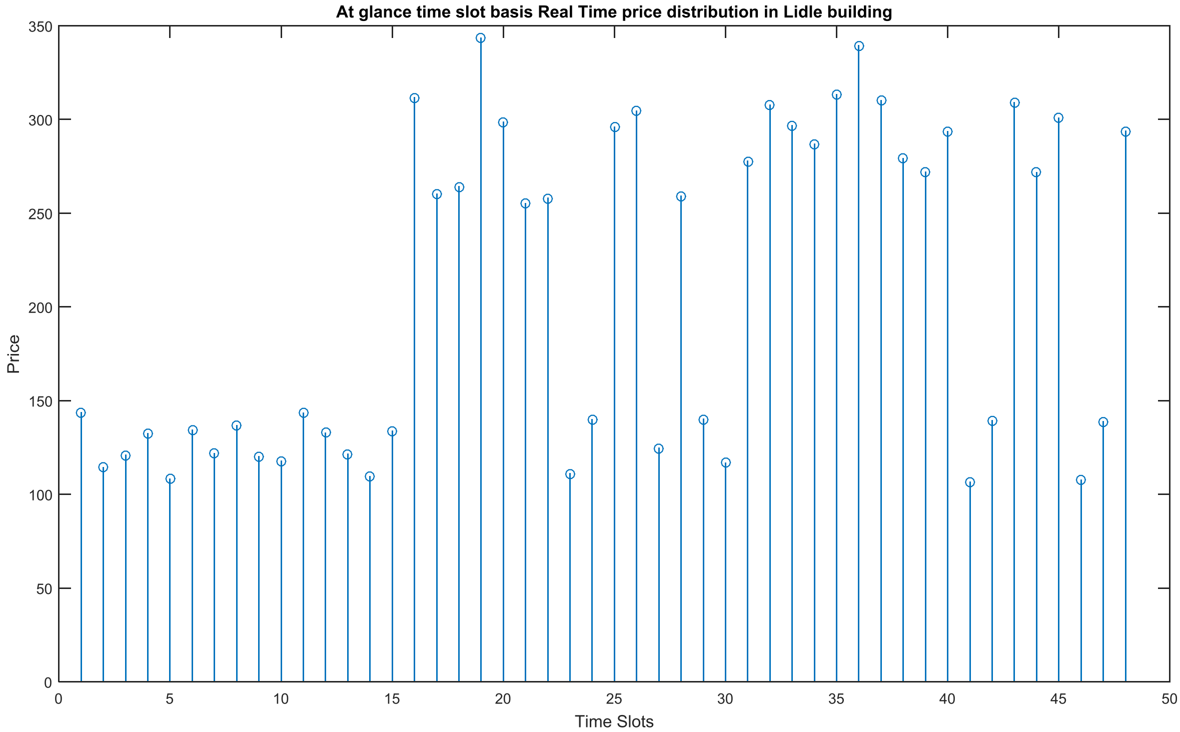


Figure 48: **Time slot basis real-time price distribution in the Lidle building**

The Johnson building RT price distribution is shown in figure 86. The RT price is charged by load consumption on a real-time basis. Some of the time slots are highly charged. For example, time slot numbers 11, 19, 32 means 5 am, 9 am, 3.30 pm, because they exceeded the threshold load and the RT price was high.

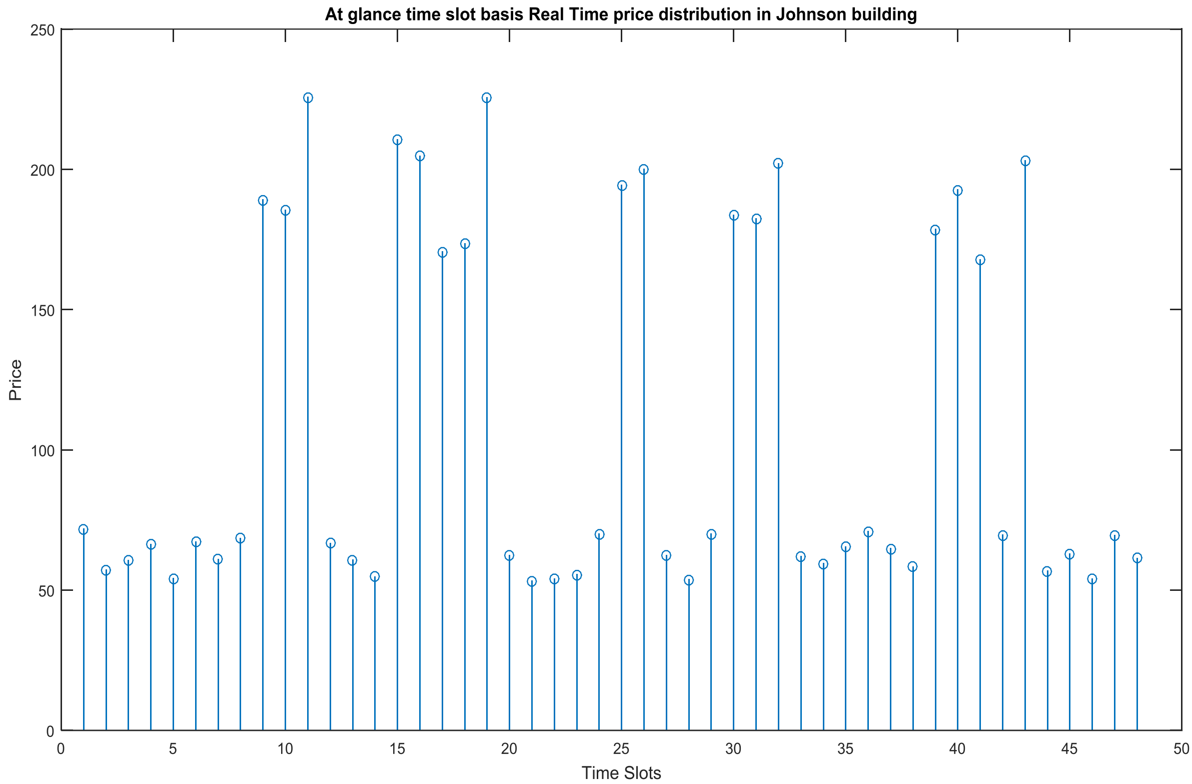


Figure 49: **Time slot basis real-time price distribution in the Johnson building**

The Campus building RT price distribution is shown in figure 87. The RT price is charged by load consumption on a real-time basis. Some of the time slots are highly charged. For example, time slot numbers 19, 24, 29, 36 means 9 am, 11.30 am, 5.30 pm, because they exceeded the threshold load and the RT price was high. So, 7.30 am to 6 pm, this building was charged with a high RT price. However, it reduced the bill.

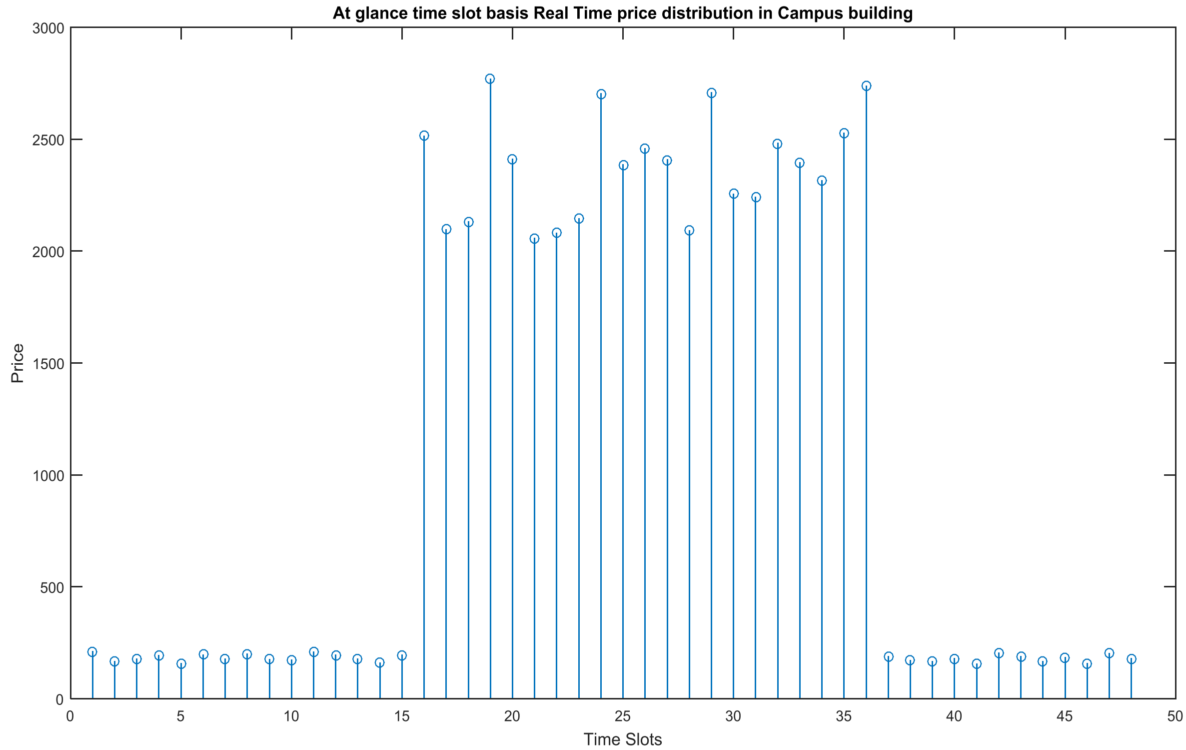


Figure 50: Time slot basis real-time price distribution in the Campus building

Similarly, the Putteridge Bury building RT price distribution is shown in figure 88 (Appendices). The RT price is charged by load consumption on a real-time basis. Some of the time slots are highly charged. For example, time slot numbers 19, 24, 29 means 9 am, 11.30 am, 2 pm, because they exceeded the threshold load and the RT price was high. Therefore, from 6 am to 5 pm all time slots were charged at a high price and the rest of them at RT low price, so the whole building saved money.

5.1.9 Real-Time Price difference from flat-rate price without considering users' response

In this section, we have shown the real time basis price differences in the different time slots. Most of the figure kept in the appendices and some of the dissimilar figures represent the impact on different buildings. For instance, the graphical representation in the figure 89 shows most of the time slots for the Sanctuary building have to an increased price on a real-time basis compared to a flat-rate price. In time slot number 39, 7 pm, it significantly lost because of its disproportionate load profile. We would suggest that users shift their load from the time slots with higher prices (when compared to the off-peak pricing position). This would help to reduce the PAR, which is our target. The green dotted line shows the average difference. This positive average means that this building would experience significant cost savings. Similarly, overall in the figure 92 (Appendices), St Pauls Place, they increased the price, but they have lost in the 7.30 am in the morning. However, it gains price significantly. St Pauls Place is a medium-size building where PAR is similar to overall PAR, but it is still above the targeted PAR. It has a positive average as the green dotted line is in the positive quadrant. Most of the time slots gain the price.

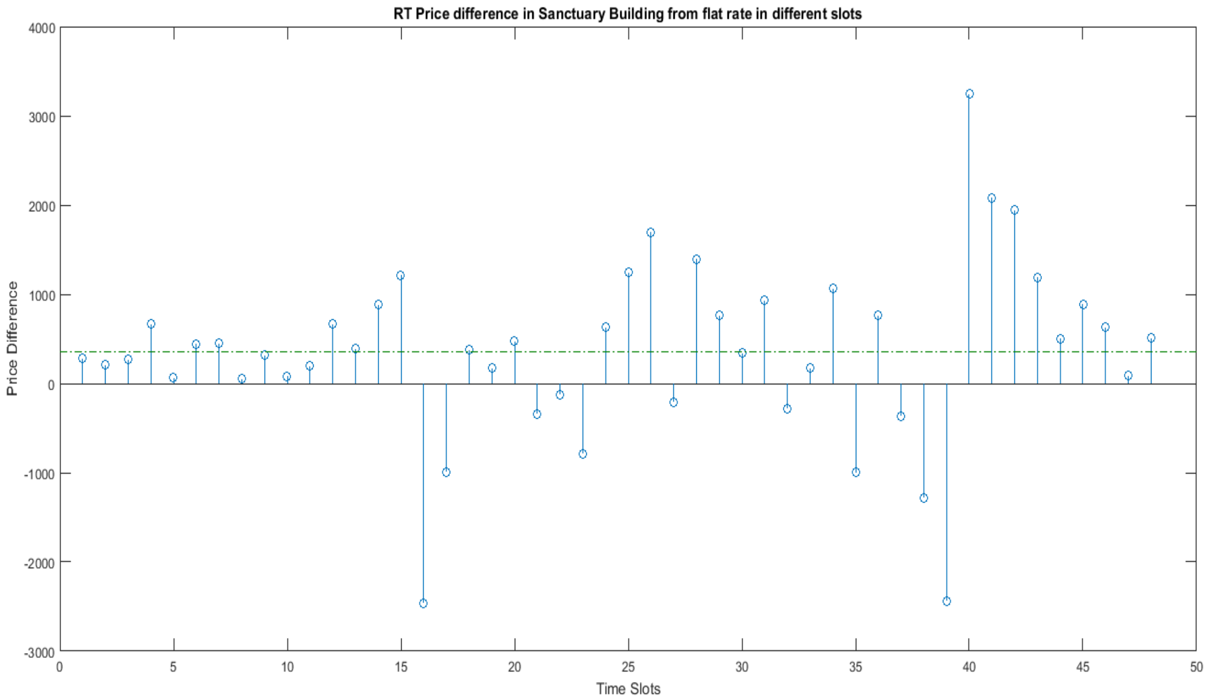


Figure 51: **RT Price difference in the Sanctuary building from flat rate in different slots**

The Castle View House RT price benefits the buildings is shown in the figure 90 (Appendices). They lost in 3.30 pm, mostly 7 pm, 9 pm and 11 pm. We could suggest that if they can shift their load from those slots to suggested slots that they would benefit more when compared to a flat-rate price. The line is positive in average. This building also experiences cost savings.

In some cases like Mowden Hall which is shown in the figure 91, they have benefitted from a lower price in time slots 6.30 am, 7.00 am, 6.00 pm, 6.30 pm and they lost in 7.30 am, 3.30 pm, 5.30 pm significantly, however, overall it did lose 0.006% which is insignificant. As we mentioned, the building has a high PAR. This green line shows the negative average which means it experiences an insignificant price rise, and they would save money after one month. We will discuss this in section 5.2. Similarly, the Johnson building of the UoB shown in the figure 95 (Appendices), significantly lost in most of the time slots like in numbers 9–11, 15–19, 30 and 41 that means at 4.00 am to 6 am, 7 am to 9.30 am, 3 pm and at 8 pm; other than these, it gains some other time slots, too. However, its price difference is sometimes positive and sometimes negative, after all its average price difference is negative and it may increase the bill. The Stephenson building of the UoB shown in the figure 100 (Appendices) gains significantly in most of the time slots and lost in other time slots, in particular, time slot numbers 11, 16 to 18, 33 and 47 that means at 5.00 am, 7.30 am to 9 am, 4 pm and 11 pm. However, its price difference is mostly negative same as above. After all, its average price difference is negative, which indicates this building increased its bill.

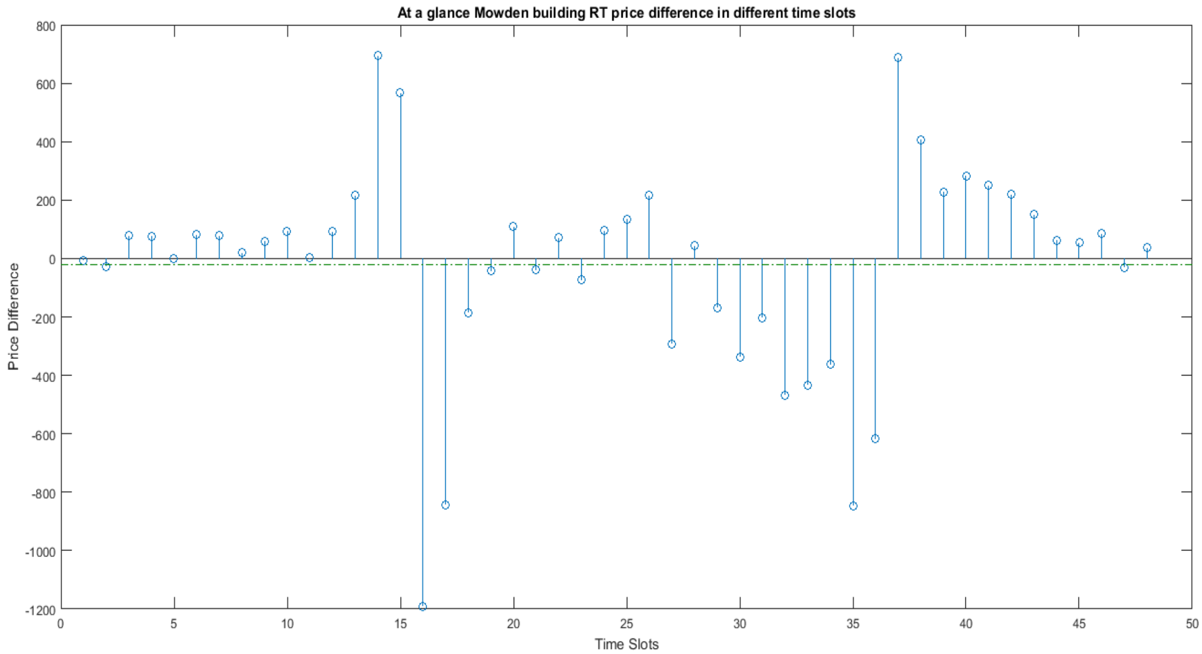


Figure 52: **Price difference in Mowden Hall from flat rate in different time slots**

In the same manner, the Paget building of the UoB shown in the figure 101 (Appendices) lost in some time slots and gained in other time slots. It lost in time slot numbers 11, 15, 27 and 47 that means at 5.00 am, 7.00 am, 1 pm and 11 pm; other than these; it lost in some other time slots too. However, its price difference is marginally negative. After all, its average price difference is marginally negative, which indicates this building lost a little amount of its bill or similar to flat-rate price.

The Lidle building of the UoB (in the figure 94), this building significantly lost in time slot numbers 16 and 44 that means at 7.30 am and 9.30 pm; other than these, it lost in some other time slots too. However, its price difference was sometimes positive and sometimes negative, after all its average price difference is positive and it reduced the bill. Similarly, the LRC building from the UoB shown in the figure 93 (Appendices), time slot numbers 16 and 17 means at 7.30 am to 8.30 am it lost price and also in time slot number 35 means at 5 pm. However, this building gains price overall because its average price difference is positive which is displayed on the green dotted line.

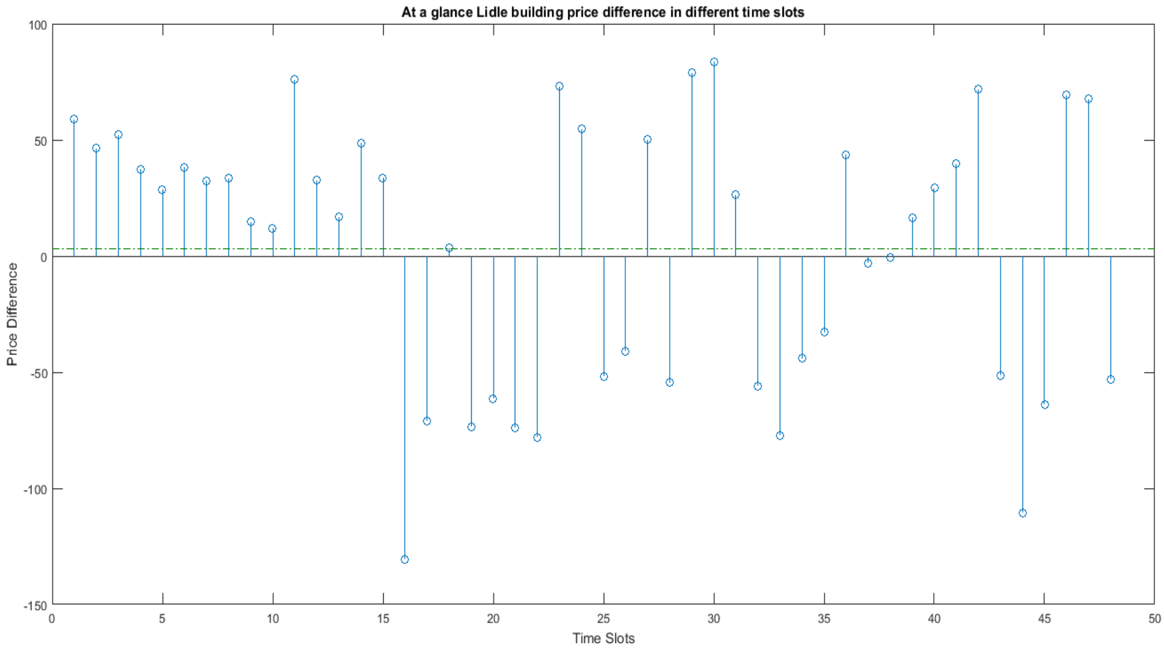


Figure 53: Lidle building price difference in different time slots

The Campus building of the UoB shown in the figure 96 (Appendices) gains significantly in most of the time slots and lost in the different time slots like 16-23 that means at 7.30 am to 11.30 am, other than these, it lost in some other time slots too. However, its price difference is mostly positive. After all, its average price difference is positive, and it decreases the bill. The Putteridge Bury building of the UoB shown in the figure 97 (Appendices) that lost the price in the time slots 13 to 17 significantly, it means at 6 to 8.30 am. But, it gains most of the time slots. Its average price difference which slows with the green dot lines is positive. It saves the bill.

The Scott building of the UoB (in the figure 98) gained significantly in most of the time slots and lost in other time slots, in particular, time slot numbers 17, 23 and 44 that means at 8.00 am, 11.00 am and 9 pm, other than these; it lost in some other time slots too. However, its price difference is mostly positive. After all, its average price difference is positive that indicates this building reduces its bill.

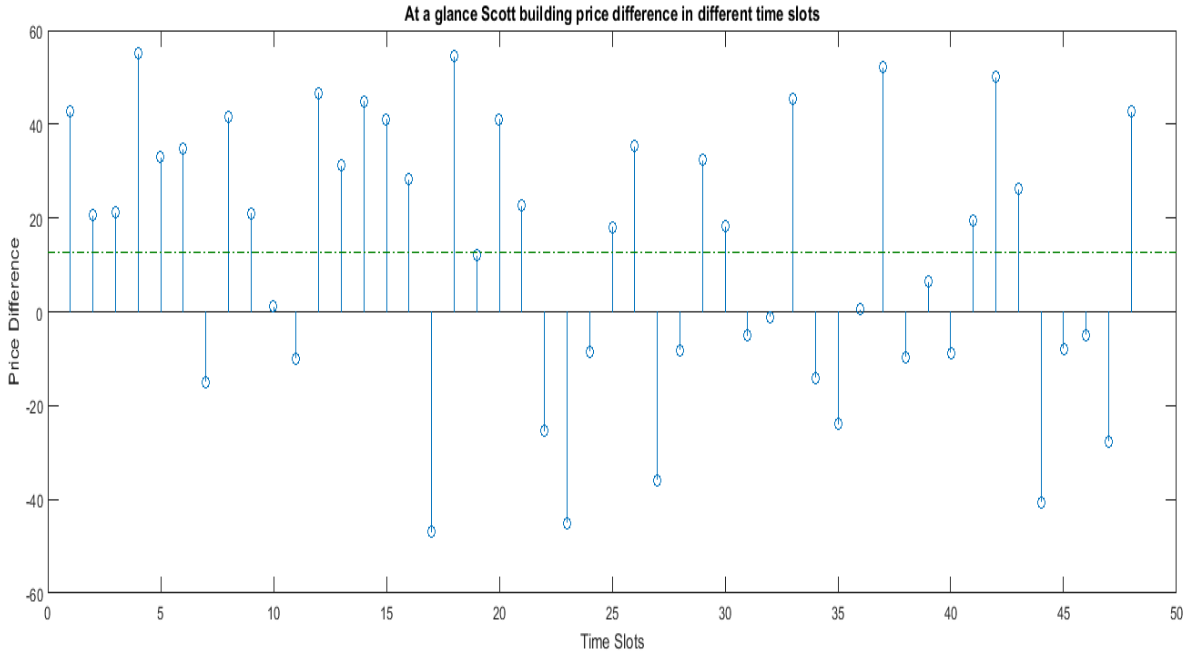


Figure 54: **Scott building price difference in different time slots**

In the same manner, the Stainiers building of the UoB shown in the figure 99 (Appendices) gained significantly in most of the time slots and lost in the other time slots, in particular, time slot numbers 11, 23 and 35 that means at 5.00 am, 11.00 am and 5 pm, other than these; it lost in some other time slots too. However, its price difference is mostly positive. After all, its average price difference is positive, which indicates this building reduced its bill. Similarly, the Park Square building of the UoB shown in the figure 102 (Appendices) gained significantly in most of the time slots and lost in other time slots, in particular, time slot numbers 16 and17 that means at 7.30 am to 8.30 am; other than these; it lost in some other time slots too. However, its price difference is highly positive. After all, its average price difference is positive, which indicates this building saves a huge amount of its bill.

5.1.10 Daily basis Load Shifting Suggestions in different buildings

In accordance with the previous day total energy load consumption, the price suggestion unit would make a half-hourly suggestion for the next day. This would include how much load they can shift from one time slot to another based on their threshold load consumption. The algorithm is able to calculate, on a real-time basis, for each of the buildings and make a suggestion for each. The algorithm starts by filling the lowest possible consumed load in the particular time slot and makes a surplus load, and the whole process continues until it makes a threshold-based load by shifting the load from one slot to another.

This graphical representation (figure 103) shows the amount of reduced load (represented by downward bars) and the amount of increased load (represented by the upward bars). Energy users can therefore understand how much energy should be reduced in particular time slots in order to achieve cost savings. The algorithm generates suggestions for each building. A load shifting suggestion signal is generated for each user through the price suggestions unit.

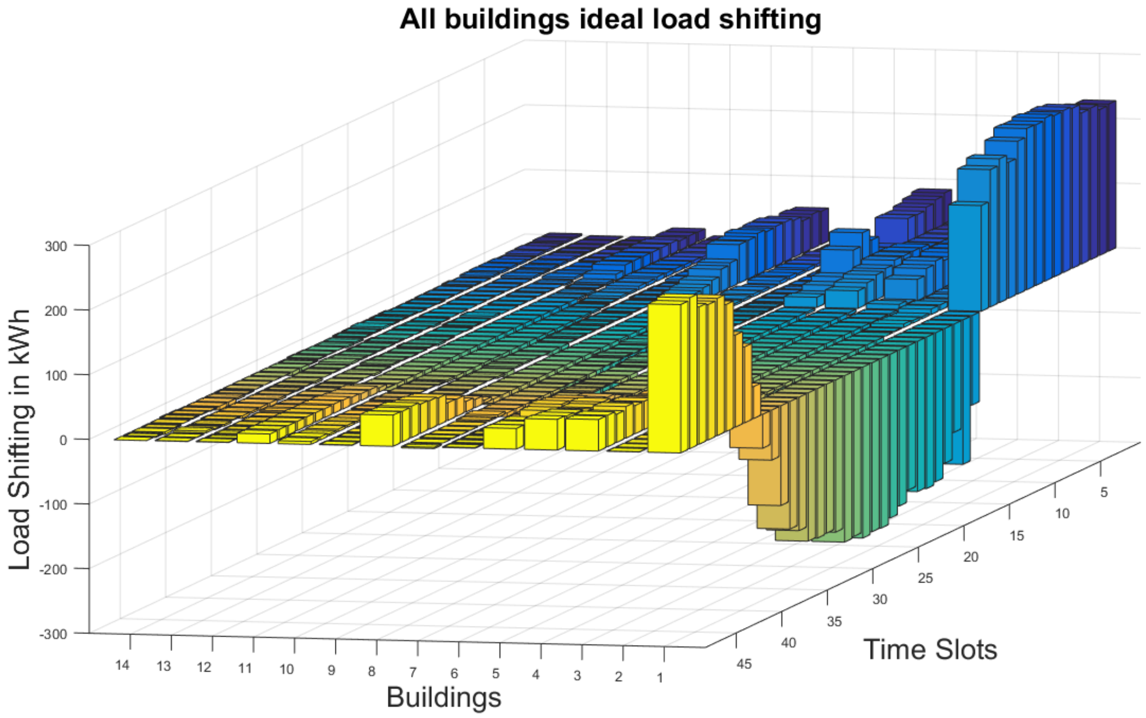


Figure 55: **Load shift suggestions per building per time slot**

The graphical representations below shows the 14 different price suggestions as we have tested the algorithm on 14 different buildings. Most of the figures kept in the appendices and some of them shown in the main thesis to understand the variability of the price suggestion. Every building is different. Price suggestions are different too. If we have million of customers then millions of price suggestions would be implemented through the algorithm. Our algorithm suggests shifting their load based on a particular building's threshold. The yellow bars of this graphical representation show that Energy users can shift their energy in particular half-hourly time slots. The downward yellow bar guides the users to increase the amount, and the upward yellow bar guides the users to decrease the amount of energy.

For the building 1 which is shown in the figure 104, it consumes energy mostly in the daytime from 7.00 am to 4.30 pm. Its average consumption is more than 400 kWh; the downward yellow bar indicates to users that the amount of energy usages they can increase in that particular time slot. The upward yellow bar shows that amount of energy usages they should decrease to reduce their bill.

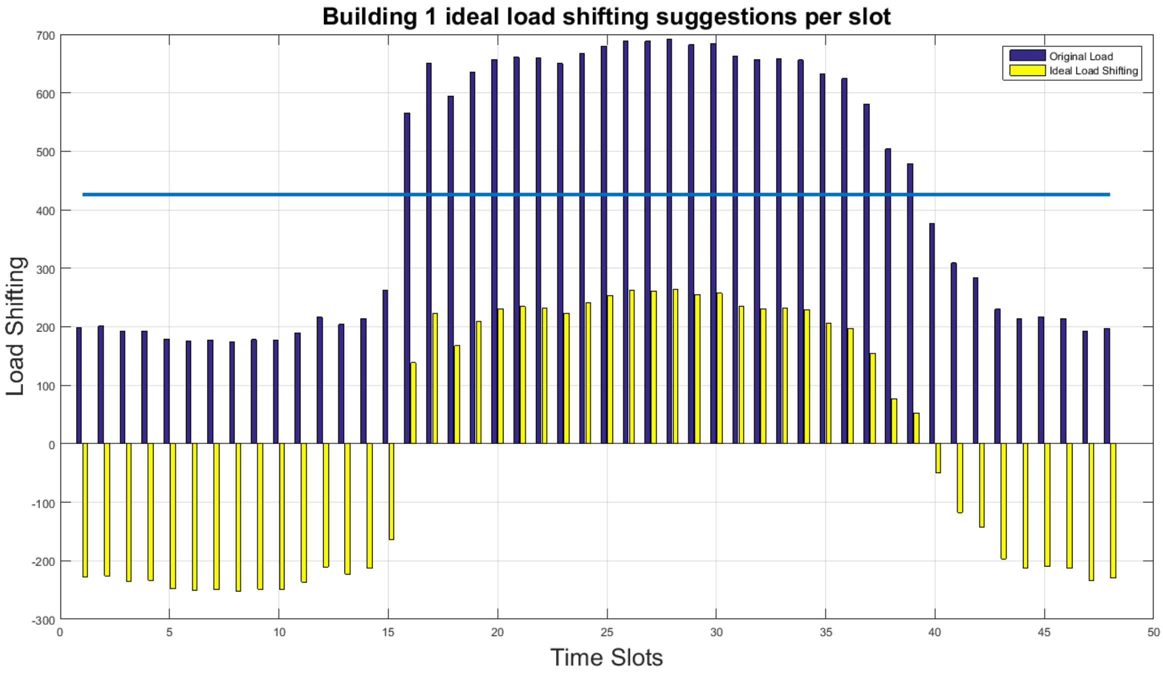


Figure 56: **Real-time ideal load shift suggestion per time slot for building 1**

Similarly, in building 3, figure 106 (Appendices) shows that its average load is more than 70 kWh. In accordance with their consumption, they need to reduce their load at 10:00 am by almost 60 kWh, 65 kWh at 10:30 am, and 70 kWh at 11:00 am, and so on. In the same manner, the building 4, figure 107 (Appendices) shows that its average energy consumption is nearly 150 kWh. Their excess loads are between 150 to 200 kWh from 11:00 am to 3:00 pm. The PSU would suggest those loads move to either in the morning or afternoon. In building 8, figure 111 (Appendices) shows that there is above the energy consumption from 10:00 am to 12:00 pm. The PSU would suggest shifting that load to below the average load in time slot numbers 1–15 that means 1 am to 7 am and also in the night time which is from time slot numbers 40–48 that means 8 pm to 12 am. In building 11, figure 114 (Appendices) shows that they are above their average energy consumption from 7:00 am to 12:00 pm. The PSU would suggest they load those spaces below the average load. This building has to shift load from midday to the morning or afternoon. It needs to increase some load in the early morning and afternoon times. It shows how much energy it needs to reduce or increase in particular time slots.

In building 2, figure 105 shows differently and energy consumption mostly from 10:00 am to 5:00 pm above the average. Their average consumption is more than 25 kWh. They can shift their load by the suggestion made. They need to reduce the energy load mostly at 11:30 am, 1:00 pm and 2 pm and shifting to 7:00 am and 7:30 am time slots. The PSU suggests shifting their above average load.

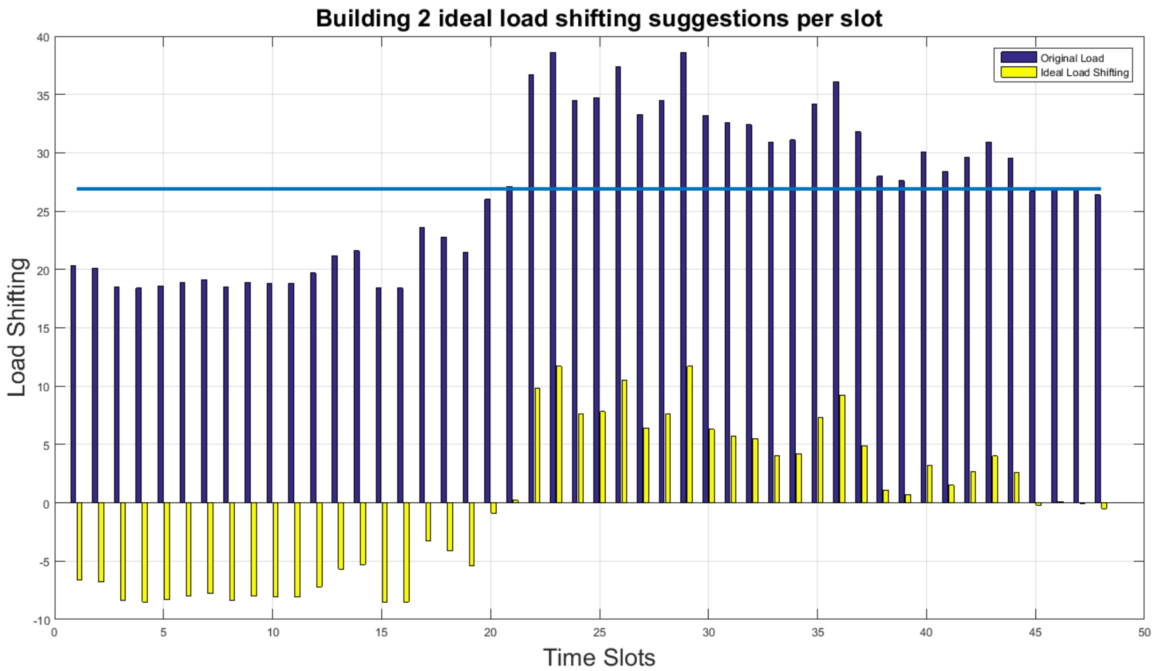


Figure 57: **Real-time ideal load shift suggestion per time slot for building 2**

In building 5, figure 108 shows that it has 100 kWh threshold, their energy consumption is above the average at 12:00 pm to 1:30 pm and then dropped, again above the average at 2:30 pm to 4:00 pm. PSU would suggest those load should be shifted to not morning or afternoon.

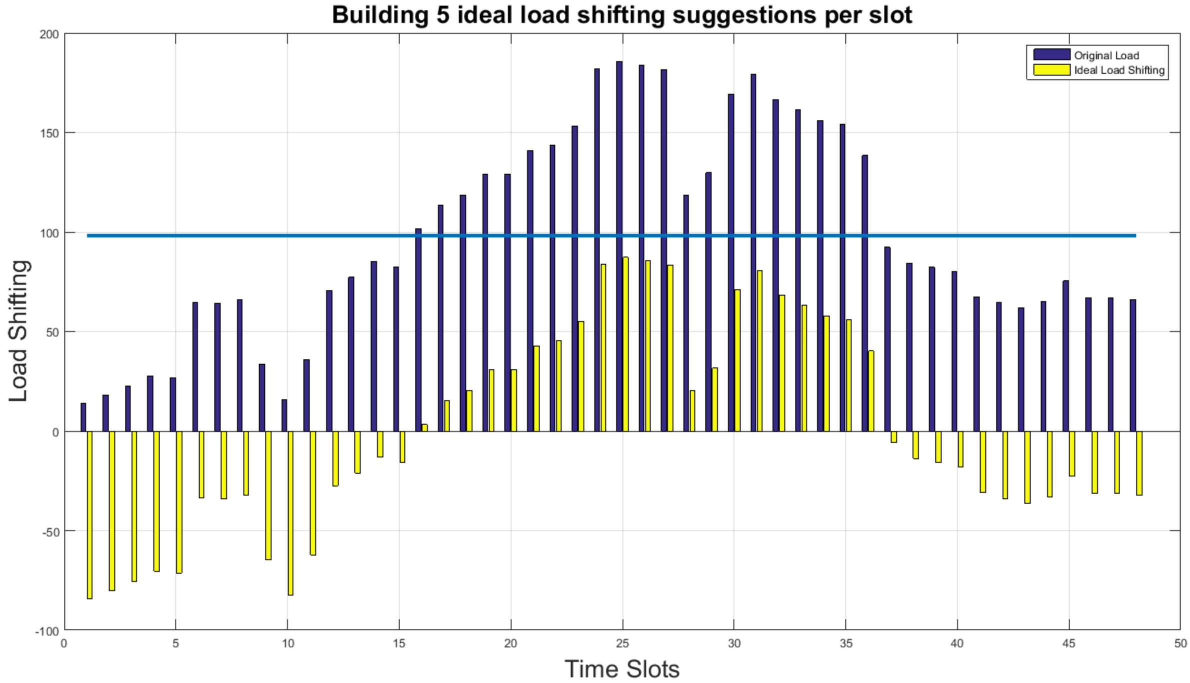


Figure 58: Real-Time Ideal load shift suggestion per time slot for building 5

In building 6, figure 109 shows that its energy consumption is significantly above the average from 12:00 pm to 1:00 pm, and 3:00 pm to 3:30 pm. The PSU would suggest those loads shift anywhere that is below the average, not in the morning or afternoon, rather in different time slots in the whole day in similar fashion.

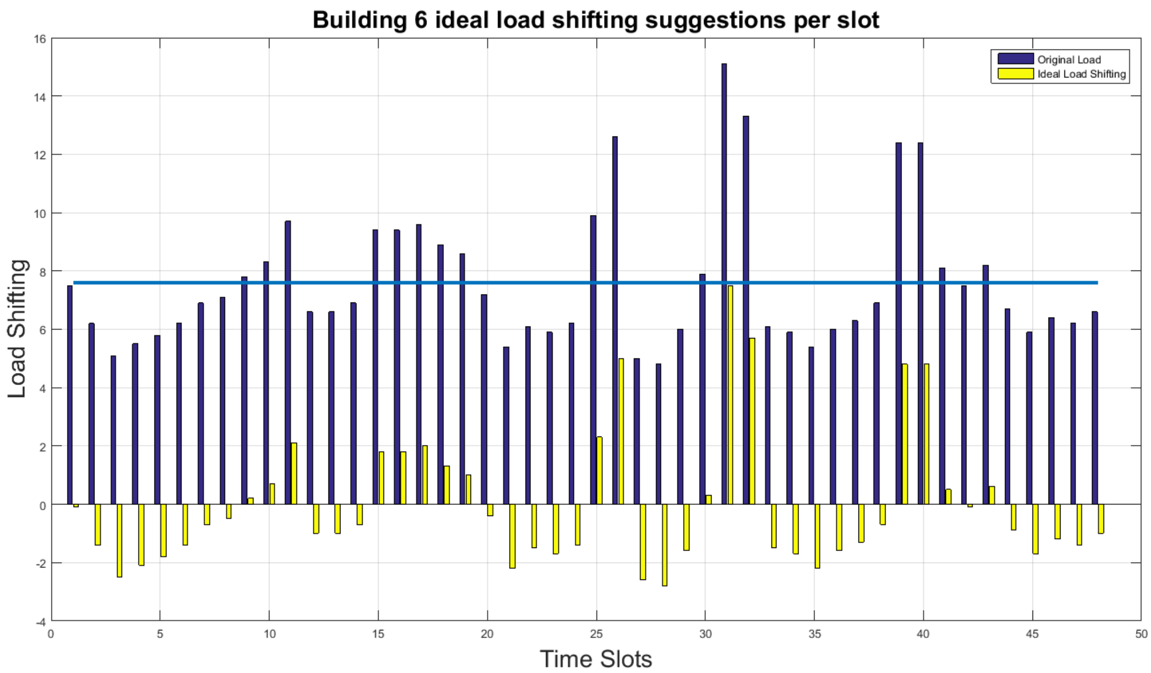


Figure 59: Real-time ideal load shift suggestion per time slot for building 6

Similarly, in building 7, figure 110 (Appendices) shows that there is above average energy consumption from 3:00 pm to 3:30 pm and 5:00 pm to 7:00 pm. The PSU would suggest those loads should be shifted to where below the average energy consumption is, mostly in the morning and its particular time slots. In the similar pattern, in building 9, figure 112 (Appendices) shows that there is above the average energy consumption at 12:00 pm, 12:30 pm, 3:00 pm, 7:00 pm and 7:30 pm. The PSU would suggest those loads to be shifted to below the average slots. This building has no particular morning or afternoon suggestions. It suggests to shift loads from 12 am to 12 pm.

In building 10, figure 113 shows that almost they are consuming an average level of energy consumption. The PSU will not suggest any significant amount of shifting. It has not got many suggestions. It is a balanced consumption building; however, in the morning, it should increase some load from the midday to the morning.

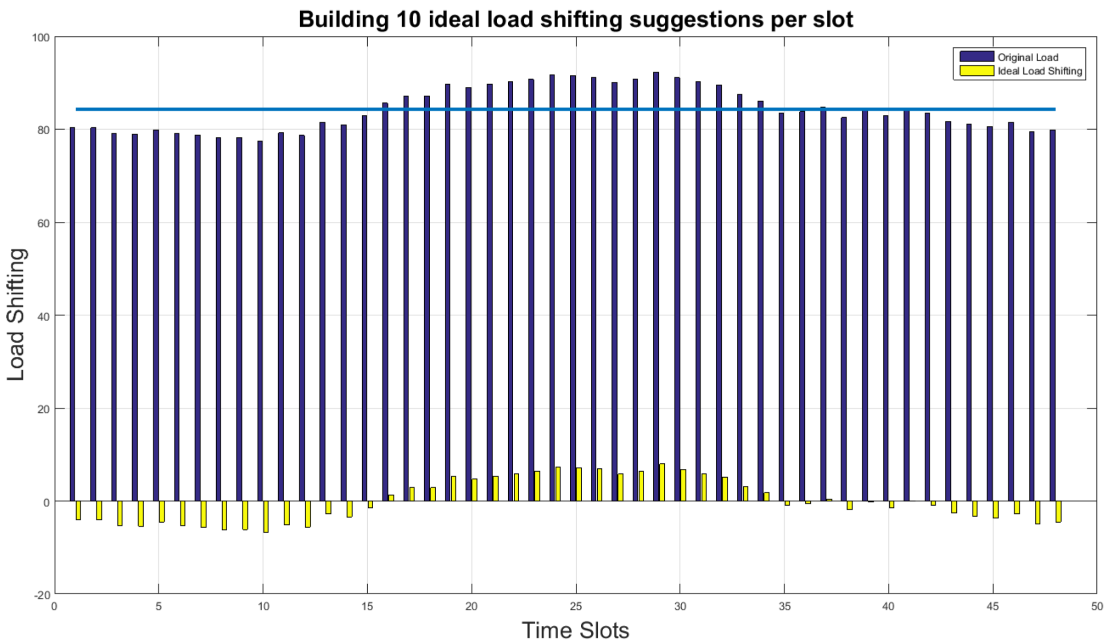


Figure 60: Real-time ideal load shift suggestion per time slot for building 10

In building 12, figure 115 shows that there are above the average loads at 5:00 am, 12:00 pm, 3:30 pm, 7:30 pm and 9:00 pm. The PSU would suggest those loads should be shifted to time slots where the load is below the average. This building has no particular pattern. It shows it needs to increase in time slot numbers 10 and 19 significantly that means 4.30 am and 9 am. Other than these, some other time slots need to readjust.

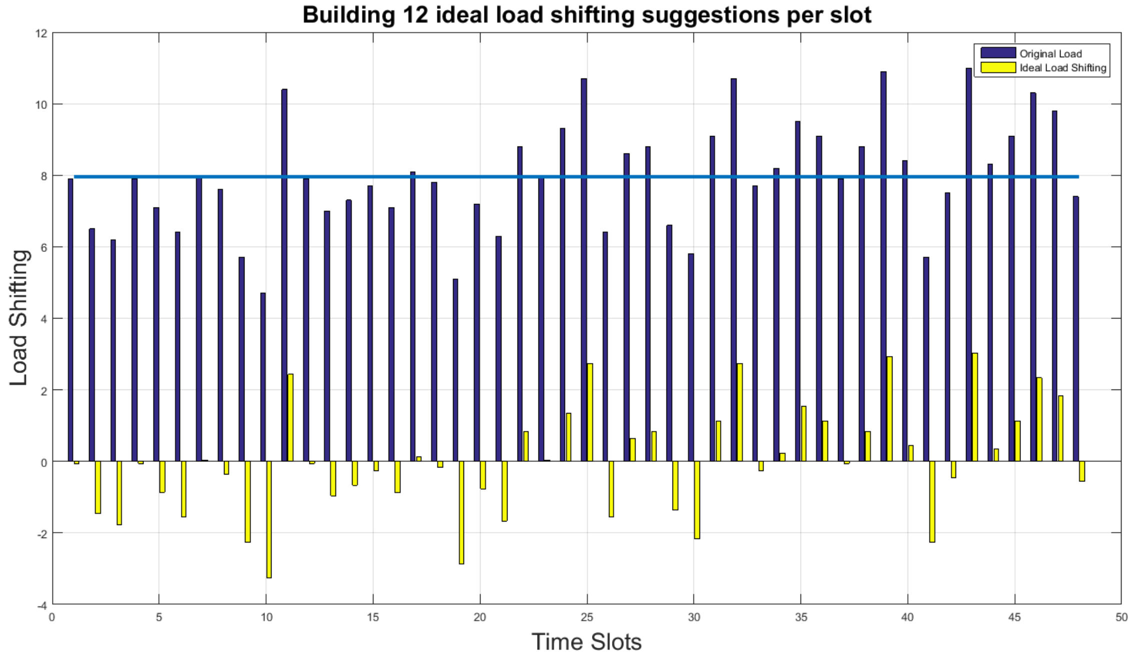


Figure 61: **Real-time ideal load shift suggestion per time slot for building 12**

Similar to building 12, the building 13, figure 116 (Appendices) shows that there are above the threshold loads at 7:00 pm and 7:30 pm. The PSU would suggest those loads should be shifted. This building load indicates that time slot numbers 3–10, 25–32 means 1 am to 5 am and 12 pm to the 4pm the user should increase their load significantly from time slots 38–42 means at 6.30 pm to 9 pm. In the similar fashion, in building 14, figure 117 (Appendices) shows that the average load at 3:00 pm, 3:30 pm, 7:00 pm and 7:30 pm significantly imbalances the overall load. The PSU would suggest those loads should be shifted. This building would shift their load from time slots 32-33 and 39–40 means at 3.30 pm to 4.30 pm and 7 pm to 8 pm to time slot numbers 1–10 means 12 am to 4 am.

5.1.11 Outcomes of load shifting after taking 20% of users' response into consideration

We measure the response from the users. It would be very difficult to ensure the data collection regarding response from the users. We made a prototype as our price suggestion unit is totally new and a novel contribution to the system. It is not possible at this stage to build a commercially viable unit. We have tested this model in simulation. We counted 20% user responses randomly and constituted the results. We assume that the above percentage of Energy users would shift their load according to the suggestions made for them by the PSU. This graphical representation (figure 118) shows the actual load shifted by the users from the Price Suggestion Unit (PSU).

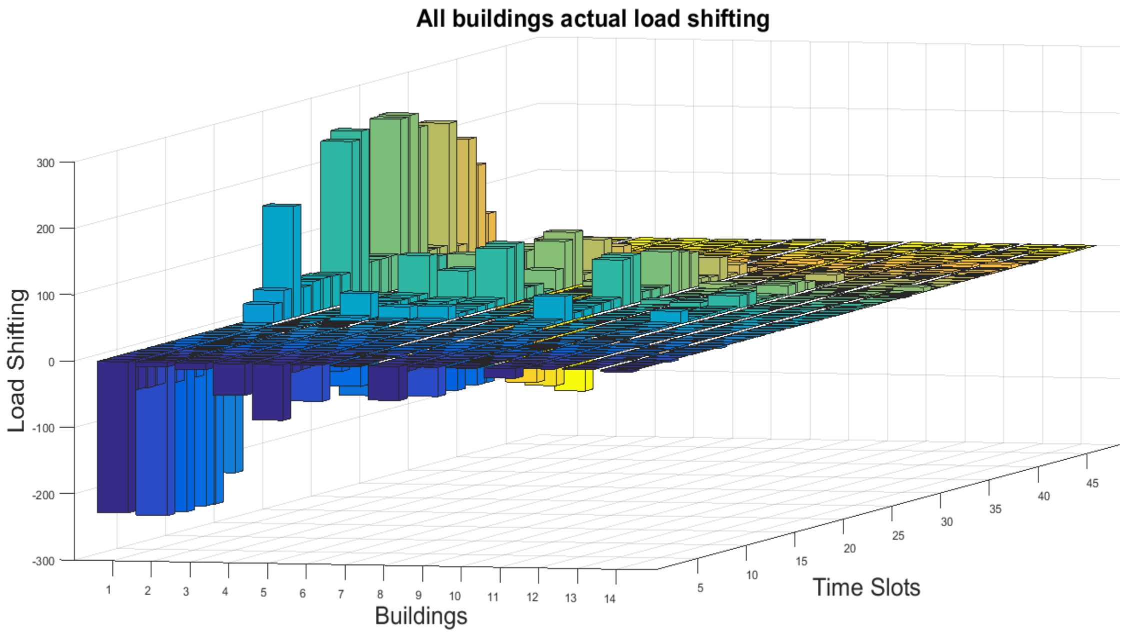


Figure 62: **The load shifting Scenario after 20% of users' response to consideration**

This research shows that at least the above percentage of users might respond as some other research shows that not many people would be interested in shifting their load. This load shifting assists in reducing the Peak-to-Average Ratio (PAR) which is important as EP savings depend on PAR.

5.1.12 All buildings Half-Hourly load scenario after Load Shifting

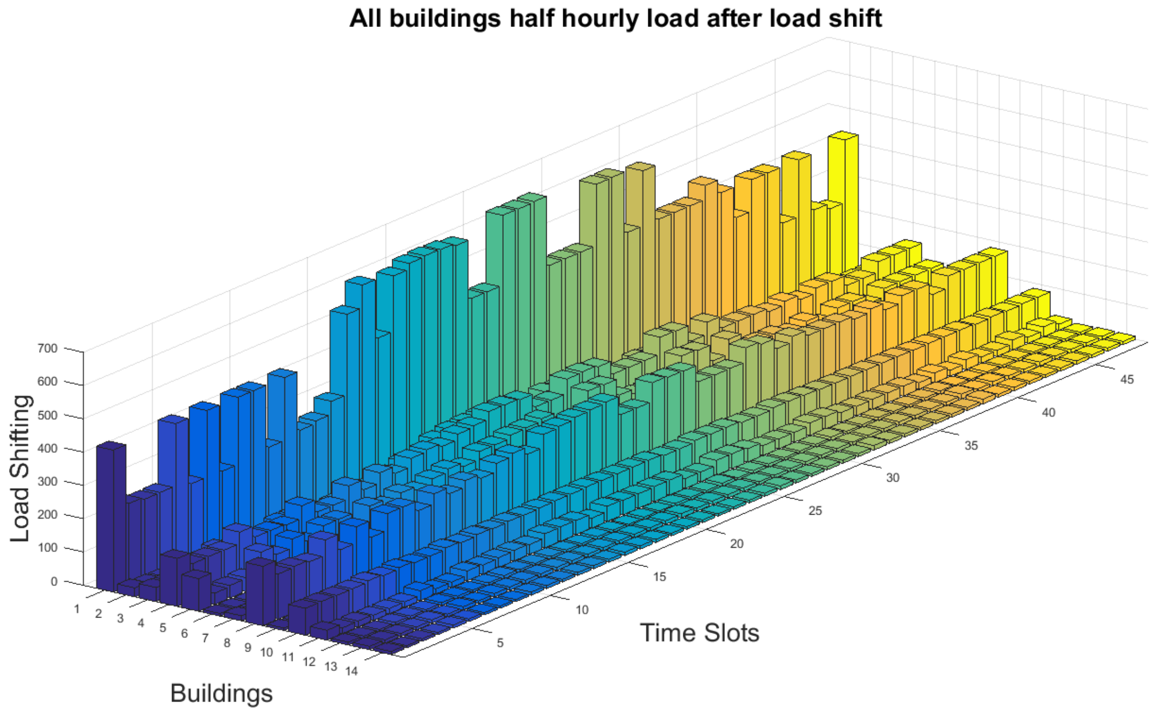


Figure 63: All 14 buildings Half-Hourly load scenario after Load Shifting

This graphical representation shows what would be the latest scenario after load shifting. Every building behaves differently. In some of the time slots, the users responded and in some of them not. However, that helps to reduce overall PAR. Our Real-Time Pricing algorithm addresses the issue if users do not respond. Still, they are better off and have reduced price regarding flat-rate pricing.

5.1.13 Time slot description

Figure 120 shows how the time slots were allocated for different times. The whole day has been divided into 48 time slots starting from 12:00 am. Every half-hour counts as one time slot in the day. 12:00 am to 12:30 am would be the first time slot, 12:30 am to 1:00 am is the second time slot and up until the last time slot which is 11:30 pm to 12:00 am. Energy consumption is counted within this half-hour.

Slot 1	Slot 2	Slot 3	Slot 4	Slot 5	Slot 6	Slot 7	Slot 8	Slot 9	Slot 10	Slot 11	Slot 12	Slot 13	Slot 14	Slot 15	Slot 16	Slot 17	Slot 18	Slot 19	Slot 20	Slot 21	Slot 22	Slot 23	Slot 24
00:00	00:30	01:00	01:30	02:00	02:30	03:00	03:30	04:00	04:30	05:00	05:30	06:00	06:30	07:00	07:30	08:00	08:30	09:00	09:30	10:00	10:30	11:00	11:30
Slot 25	Slot 26	Slot 27	Slot 28	Slot 29	Slot 30	Slot 31	Slot 32	Slot 33	Slot 34	Slot 35	Slot 36	Slot 37	Slot 38	Slot 39	Slot 40	Slot 41	Slot 42	Slot 43	Slot 44	Slot 45	Slot 46	Slot 47	Slot 48
12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	16:30	17:00	17:30	18:00	18:30	19:00	19:30	20:00	20:30	21:00	21:30	22:00	22:30	23:00	23:30

Figure 64: Figures of half-hourly total 48 time slots in a day

5.2 Monthly basis pricing analysis

5.2.1 Summary of the monthly based price analysis

We have collected data from the University of Bedfordshire (UoB). Different companies charge at different rates, however, they charge similar flat-rate prices. For example, one of the EP in the UK charges 13.844 pence per kWh. The buildings of UoB in the UK show that they have 24-hour energy consumption in their sites. We have tested the model with the UoB on a pre-existing dataset (30 days' half-hourly basis, ten buildings).

We produced a result where we have shown that each building benefits from the proposed system: the smart meter that collects data and connects to all other appliances. We have calculated the overall Peak-to-Average Ratio (PAR) based on total load (of all buildings) from the EP's point of view. The EP would think about the total load demand from Energy users. Nonetheless, whatever the demand in particular time slots out of 48 slots, the Energy Supplier supplies the same amount of energy to meet the demand of Energy Users. To meet the users' peak demand, the Energy Supplier supplies the maximum amount of energy. We calculated what would be the ratio of peak demand and total load as PAR. We also calculated building-based PAR, so that we know individual buildings' PAR. Based on overall average energy consumption, we assume that at least we could bring down peak load to average load.

We define this as target PAR. However, we also calculated the flat-rate price; it shows users' costs are influenced by the found peak energy consumption that can be suggested to reduce to average consumption, i.e. users' would shift their load from a particular peak time slot to another slot. Real-time prices have been calculated by using a simultaneous perturbation stochastic approximation method that reduced users' bill significantly. Overall pricing is also implied on the price parameter, but because of data variability, price implied in the individual building has obtained a significant result.

In the flat-rate pricing, some of the users might be overcharged or undercharged while they respond on a Time-of-Use basis with flat-rate pricing on incentives – this will not influence users to shift their load. However, real-time pricing is the solution for them as there will not be a question of over- or undercharging for their usages. Real-time pricing is based on generation, transmission and distribution costs. We would suggest to users that if they can shift their load from the time slots they lose their price to suggested position that would help to reduce the PAR. Again, we have also used ten buildings' energy consumption data collected from the UoB. Their data includes half-hour energy usages collected through a smart meter.

Monthly data is used to show the reduction; however, day-wise suggestions made and users' need to respond time slot wise. In figure 121, the reduction of load is shown through downward bars and increased load through upward bars. The algorithm produced a real-time price that is based on a particular user's threshold load. If the user exceeds its threshold, then it would be charged the maximum rate, otherwise the minimum rate. We count 20% response in the suggestions unit, based on several types of research. **Total load is reduced to a monthly 418,962 kWh. Peak demand after load shifting is 10,159 kWh. Actual peak demand is 11,315 kWh, and average demand is 8829 kWh.**

5.2.2 All buildings monthly energy consumption

Figure 121 shows that total monthly energy load (all users) in each time slot; it shows which time slot it would be most significant to address. Peak load shows in the middle that is the most significant load incurring cost to the energy suppliers. Our model guides reduction of the peak load.

The PSU suggests how energy users should shift and where. Ideal suggestions are made for the users; however, the model does not expect everyone's response. The 3D figure 121 shows users' usages. Time slots are on the X-axis, users are on the Y-axis, energy load on the Z-axis, to understand the current scenario of the energy load occurring in the grid.

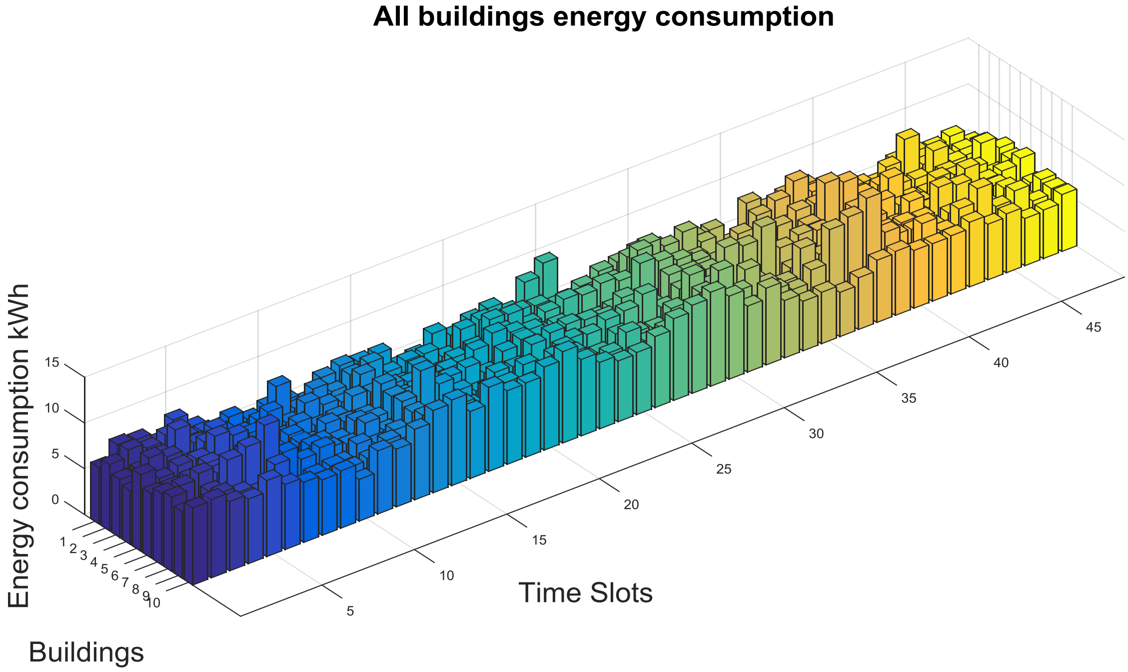


Figure 65: All buildings' monthly energy consumption

Regarding users' energy usages, users have a choice to shift their load or not. However, we considered 20% random load shift which makes the graphical representation as in figure 122. Figure 122 shows load in each of the time slots for the ten buildings for a month. The algorithm works for the best possible outcome as a whole to reduce the bill and energy providers' cost. This scenario shows overall that most of the time slots are targeted to reach average consumption.

5.2.3 All building scenario after load shifting

We have analysed load scenario once the customers shift their loads following the price suggestions. The figure 122 demonstrates that load scenario. Assume that customers used PSU and follow the price suggestions accordingly act on it.

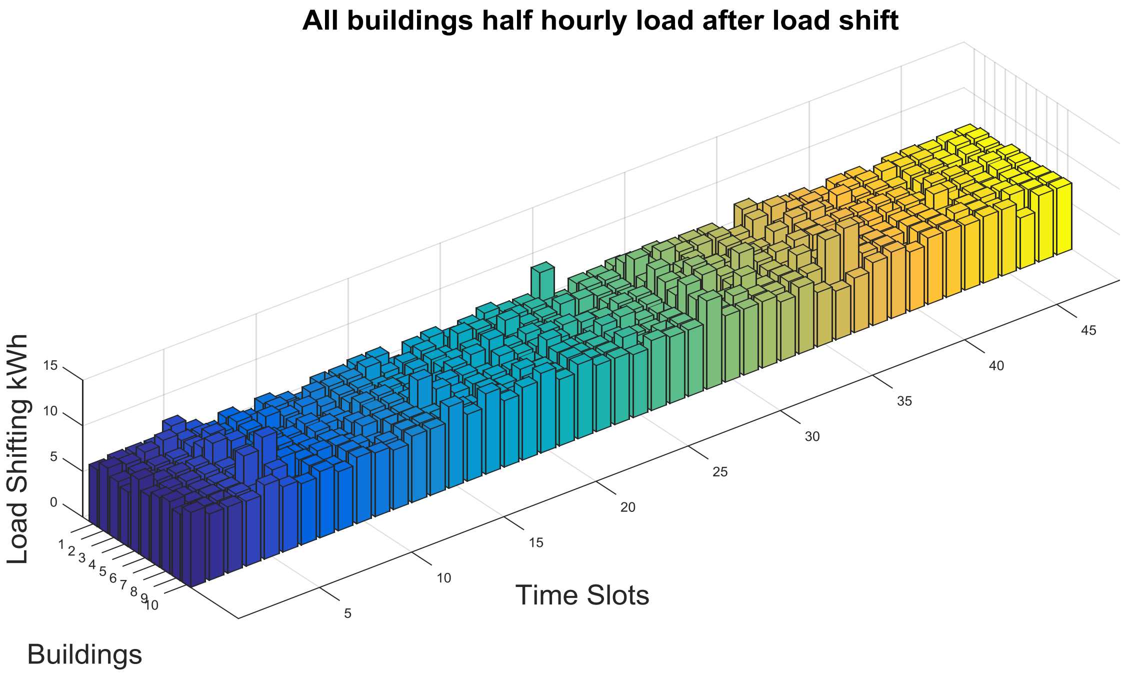


Figure 66: **All buildings' half-hourly load scenario after load shift**

5.2.4 All buildings actually load shifted

We have analysed the scenario of actual load shifted in a month. The figure 123 shows how much energy is shifted in different time slots for the ten buildings for a month. It may either reduce or increase load in the time slots. This is a random selection from the load shifting.

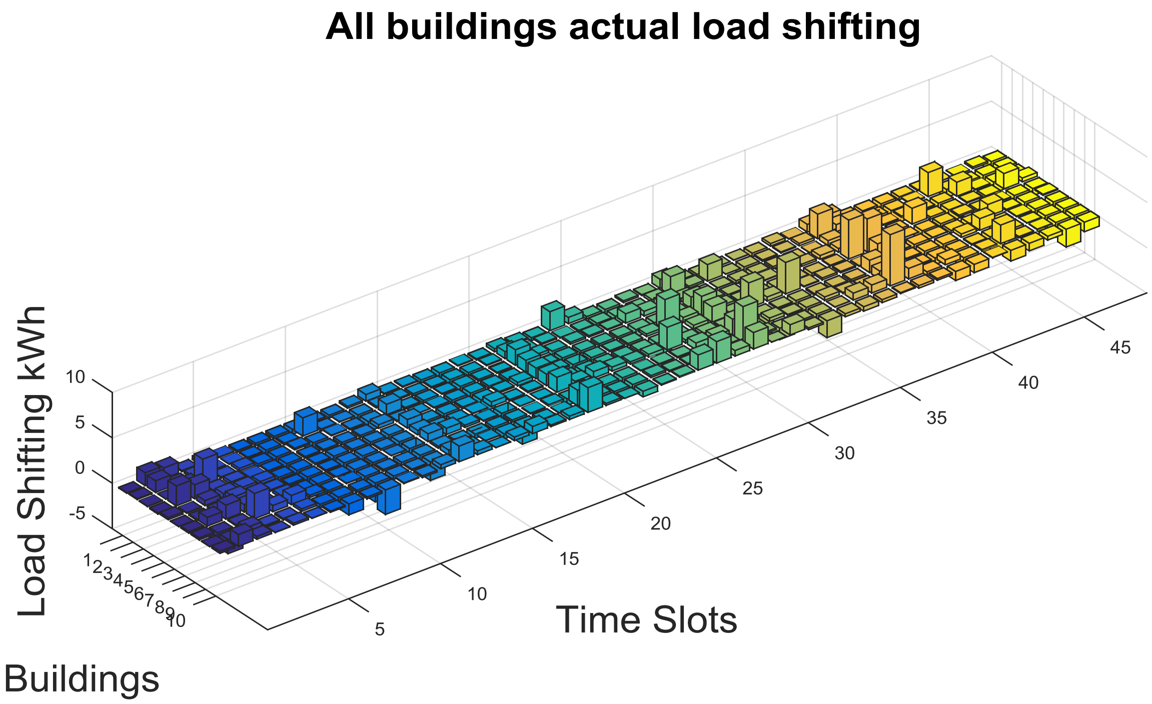


Figure 67: **All building actual load shifting (monthly)**

5.2.5 Monthly ideal load to be shifted

We analysed also what should be the ideal load shifting from the customers. In the figure 124 shows regarding threshold load how much load should be shifted ideally. This is the representation of the ten buildings of the UoB. This is also based on total load in a month (30 days).

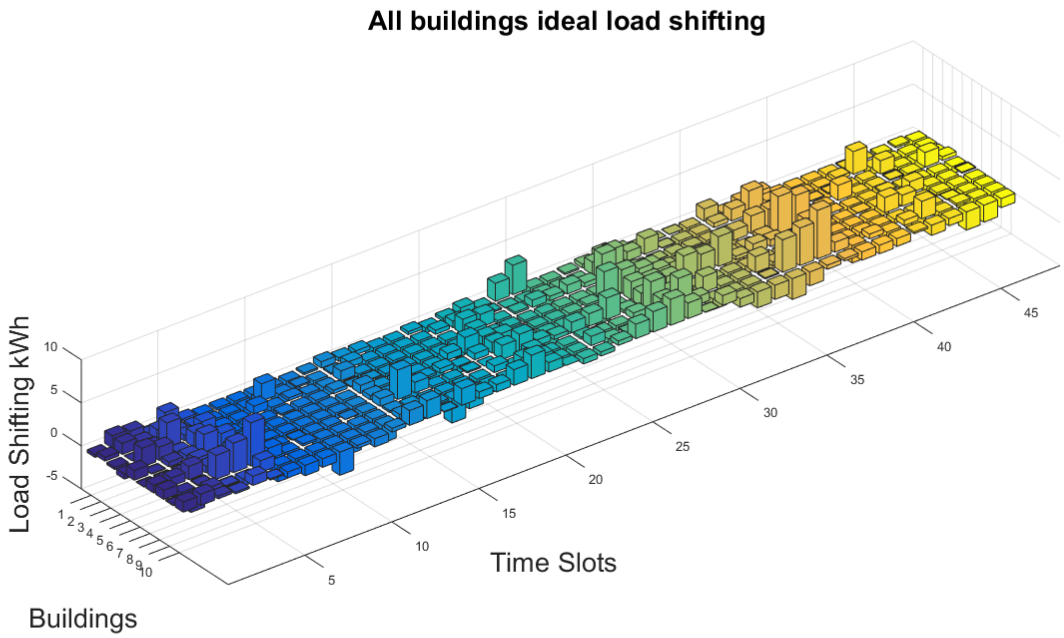


Figure 68: **All building ideal load shifting**

5.2.6 Monthly suggestions for all buildings

Our model shows that Energy users significantly reduced their monthly energy bill using real-time pricing methods. Considering the traditional price value per unit energy consumption, we have checked how much money users are spending on the real-time basis price at the end of the month. Customers will receive messages daily and monthly basis. However, they should follow the daily basis suggestions. Monthly basis suggestions would be for them to aware of the load shifting, at the end they will know the current scenario of their bills. We have shown one figure in the main thesis and find the rest of the building base analysis in the appendices.

For building 10, figure 125 shows that were they to shift their energy, as one users' energy usages lies between 7 am to 4.30 pm, the PSU would show its average consumption at 400 kWh and where to shift its energy. The Energy Users' (EU) monthly bill has been significantly reduced even without responses to the price suggestions unit. Without shifting their load, they can reduce their cost regarding the traditional price value. After load shifting, they can save more. The main power grid charges energy suppliers based on peak load. Peak load reduction benefits the energy suppliers. If all of the energy suppliers use this algorithm, the overall SG will produce less energy than the existing supply. Figure 125 shows that, per users' suggestions made by the PSU. The user interface would notify every user, and accordingly, they would respond. It shows the suggestions based on the threshold load; the building suggestions shows where to energy shift and yellow upward bars show that users need to reduce energy usage and downward bars show that users can increase energy usage. All of the graphical representation shows price reduction regarding users. On an average per day, peak demand is reduced almost 129 kWh, from 1716 kWh to 1587 kWh. Users' monthly basis reduced their bill significantly, that is by almost 3870 kWh.

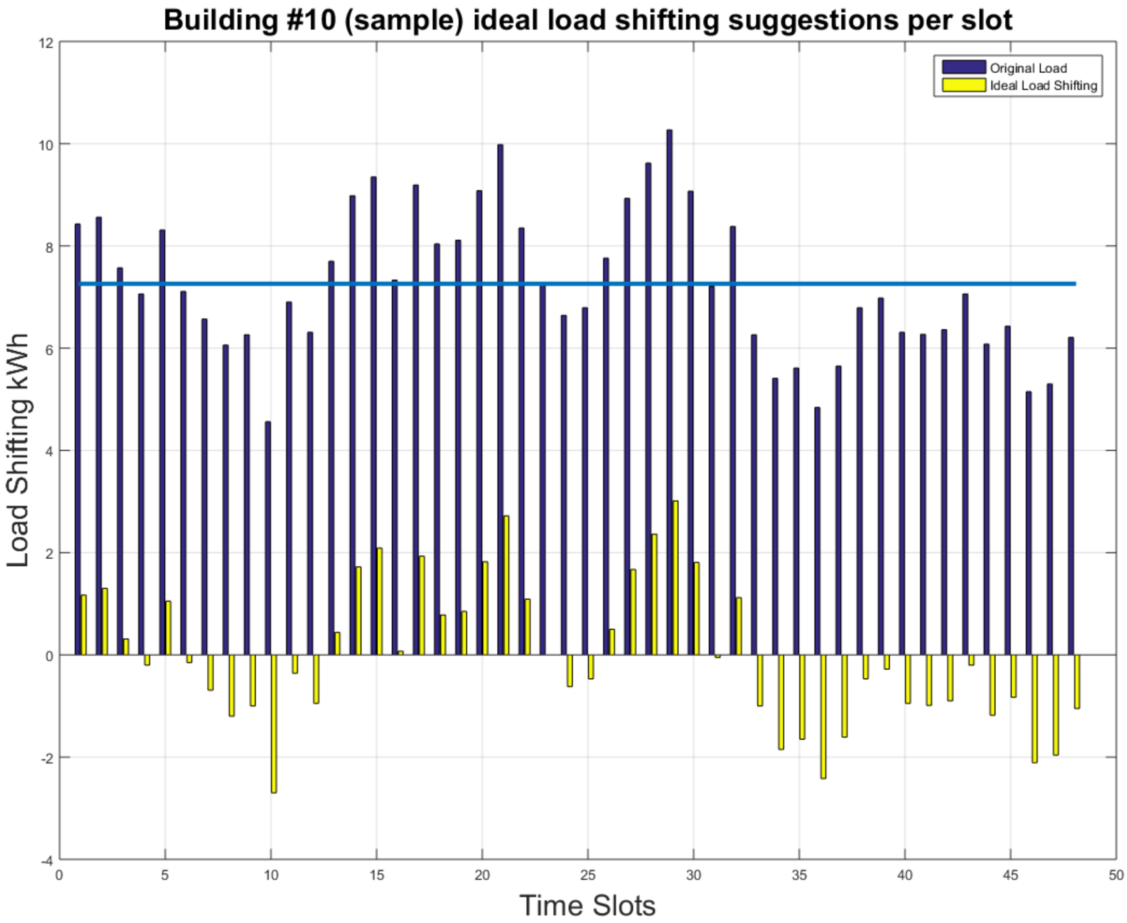


Figure 69: Building 10 ideal load shifting monthly suggestions per slot

For building 9, figure 126 (Appendices) shows where to shift their energy, as users' energy usages in time slot numbers 29–30 and 36–38 means 2–3 pm and 5.30 pm to 2.30 am were mostly above the average. They may shift their load to 3 am to 6 am. The PSU would show average consumption and where to shift the energy. Energy Users' (EU) monthly bill has been significantly reduced even without responses to the PSU. Without shifting their load, they can reduce their cost regarding traditional price value. After load shifting, they can save more. In building 8, figure 127 (Appendices) shows where to shift their energy, as users' energy usages in time slot numbers 4–7 and 29–30 means 1.30 am to 3.30 am and 2 pm to 3 pm were mostly above the average. They may shift their load to time slot numbers 1–13 means 4.30 am to 6.30 am. The PSU would show its average consumption and where to shift its energy usage. Energy Users' (EU) monthly bill has been significantly reduced even without responses to the PSU. Without shifting their load, they can reduce their price regarding traditional price value. After load shifting, they can save more.

In building 7, figure 128 (Appendices) shows where to shift their energy, as users' energy usages in time slot numbers 15, 21–22 and 25–27 means 7.00 am, 10 am to 11 am and 12 pm to 2 pm were mostly above the average. They may shift their load to time slot numbers 31–34 means 3 pm to 5.00 pm. The PSU would show its average consumption and where to shift its energy. Energy Users' (EU) monthly bill has been significantly reduced even without responses to the PSU. Without shifting their load, they can reduce their price regarding traditional price value. After load shifting, they can save more. In building 6, figure 129 (Appendices) shows where to shift their energy, as users' energy usages in time slot numbers 29–39 means 2 pm to 7.00 pm were mostly above the average. They may shift their load to time slot numbers 7–14 means 3 am to 7.00 am. The PSU would show its average consumption and where to shift its energy. Energy Users' (EU) monthly bill has been significantly reduced even without responses to the PSU. Without shifting their load, they can reduce their price regarding traditional price value. After load shifting, they can save more.

In building 5, figure 130 (Appendices) shows where to shift their energy, as users' energy usages in time slot numbers 21–31 and 38–39 means 10 am to 3 pm and 6.30 pm to 7.30 pm were mostly above the average. They may shift their load to time slot numbers 7–13 means 3 am to 6.30 am. The PSU would show its average consumption and where to shift its energy. Energy Users' (EU) monthly bill has been significantly reduced even without responses to the PSU. Without shifting their load, they can reduce their price regarding traditional price value. After load shifting, they can save more. In building 4, figure 131 (Appendices) shows where to shift their energy, as users' energy usages in time slot numbers 2–5 and 36–39 means 12.30 am to 2.30 am and 5.30 pm to 7.30 pm were mostly above the average. They may shift their load to time slot numbers 17–20 means 8 am to 10 am. The PSU would show its average consumption and where to shift its energy. Energy Users' (EU) monthly bill has been significantly reduced even without responses to the PSU. Without shifting their load, they can reduce their price regarding traditional price value. After load shifting, they can save more.

In building 3, figure 132 (Appendices) shows where to shift their energy, as users' energy usages in time slot numbers 4, 21–22 and 29 means 1.30 am, 10 am to 11 am and 2 pm were mostly above the average. They may shift their load to time slot numbers 15–20 means 7 am to 10 am. The PSU would show its average consumption and where to shift its energy. Energy Users' (EU) monthly bill has been significantly reduced even without responses to the PSU. Without shifting their load, they can reduce their price regarding traditional price value. After load shifting, they can save more. In building 2, figure 133 (Appendices) shows where to shift their energy, as users' energy usages in time slot numbers 10, 29–32 and 44 means 4.30 am, 2 pm to 4 pm and 9.30 pm were mostly above the average. They may shift their load to time slot numbers 16–19, 26, 34, 40 means 7.30 am to 9.30 am, 12.30 pm, 4.30 pm and 7.30 pm. The PSU would show its average consumption and where to shift its energy. Energy Users' (EU) monthly bill has been significantly reduced even without responses to the PSU. Without shifting their load, they can reduce their price regarding traditional price value. After load shifting, they can save more. In building 1, figure 134 (Appendices) shows where to shift their energy, as users' energy usages in time slot numbers 24–25 means 11.30 am to 12.30 pm were mostly above the average. They may shift their load to time slot numbers 9–12, and 35 means 4 am to 6 am and 5 pm. The PSU would show its average consumption and where to shift its energy. Energy Users' (EU) monthly bill has been significantly reduced even without responses to the PSU. Without shifting their load, they can reduce their price regarding traditional price value. After load shifting, they can save more.

We could suggest that if they can shift their load from those slots to suggested times, that would reduce their bill significantly. We generated different graphical representations for each of the loads of the different buildings. To determine the best price practice, real-time basis generation and distribution costs should be exposed to pricing. Vibrant, real-time pricing benefits the SG. An Energy Provider's decision on price selection would impact on the user profile. We use a round flat-rate random price, but dynamically charge on the user profile on an every half-hour basis. The EP can set their price maximum and minimum based on the threshold load on the user profile.

5.2.7 Monthly Real-Time (RT) price calculation per building

We have calculated the monthly base real-time price on different time slots per building. Figure 135 shows how real-time prices are calculated for different time slots. This charge is calculated based on the threshold load. If the load exceeds the threshold load, then a high price in that particular time slot is generated, otherwise a lower price will be suggested. This graphical representation shows the RT price distribution in different time slots.

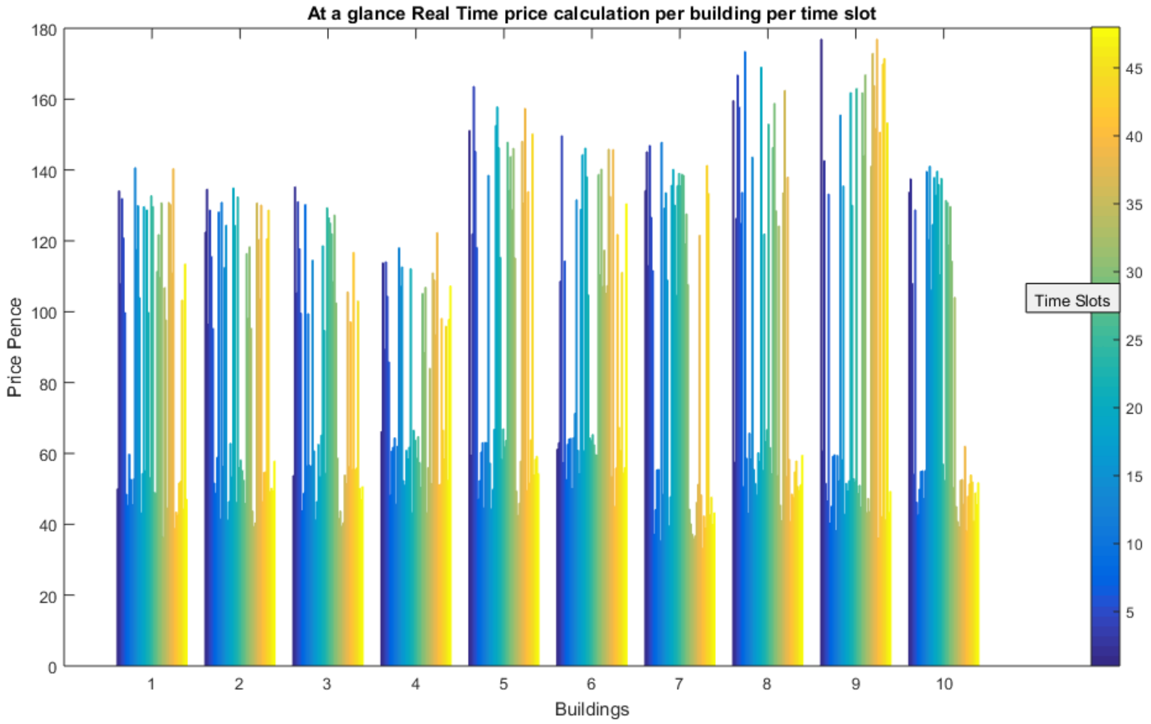


Figure 70: **Real-time price calculation per building per time slot**

5.2.8 Monthly cost per building per time slot after load shifting

We have calculated the monthly base real-time price on different time slots per building after load shift. Figure 136 shows the real-time base charged in different time slots after load shift. This charge calculated is based on the threshold load. If the load exceeds the threshold load, then it would be charged at a high price in that particular time slot, otherwise low price. This graphical representation shows the RT price distribution in different time slots after load shift.

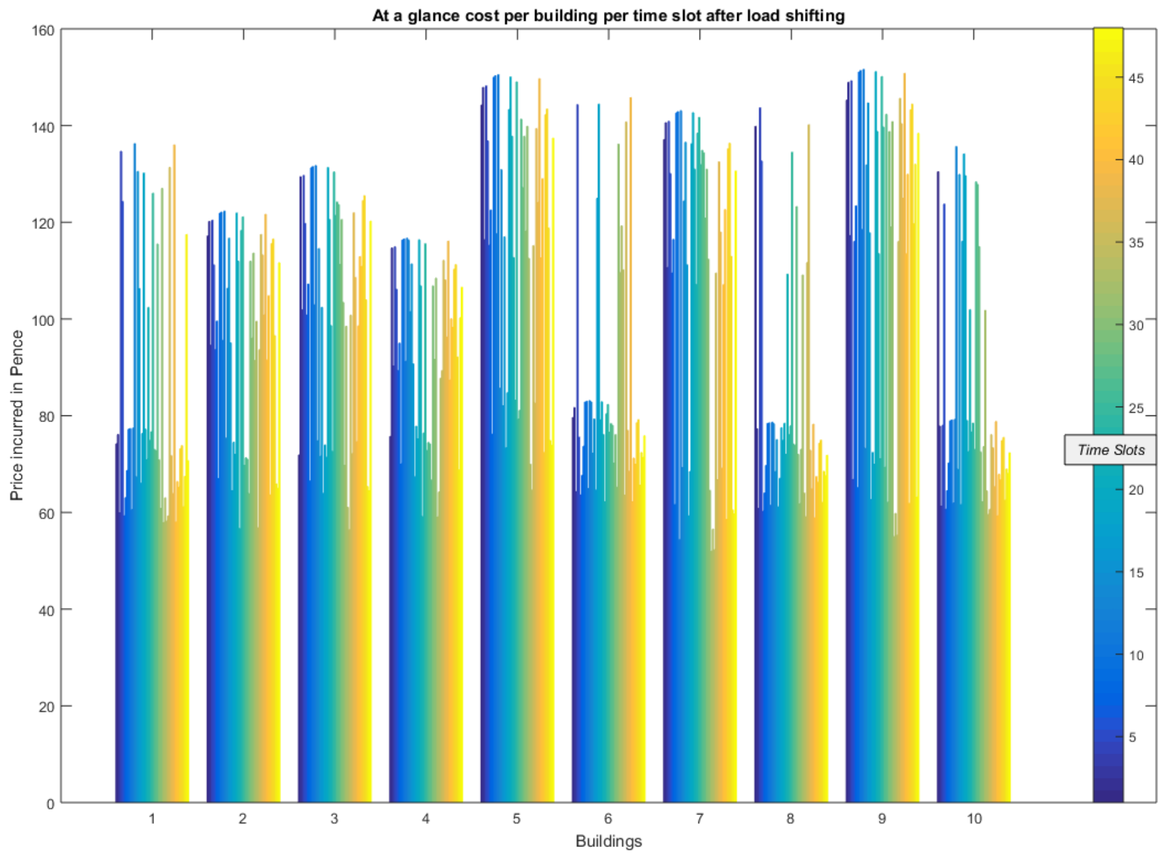


Figure 71: Cost per building per time slot after load shifting

5.2.9 Monthly load reduced after load shifting

The graphical representation in figure 137 shows how much load has been reduced after load shifting in different time slots. This is based on 30 days' load. We can see every building managed to reduce their load. Therefore their price is also reduced once the RT price system is applied.

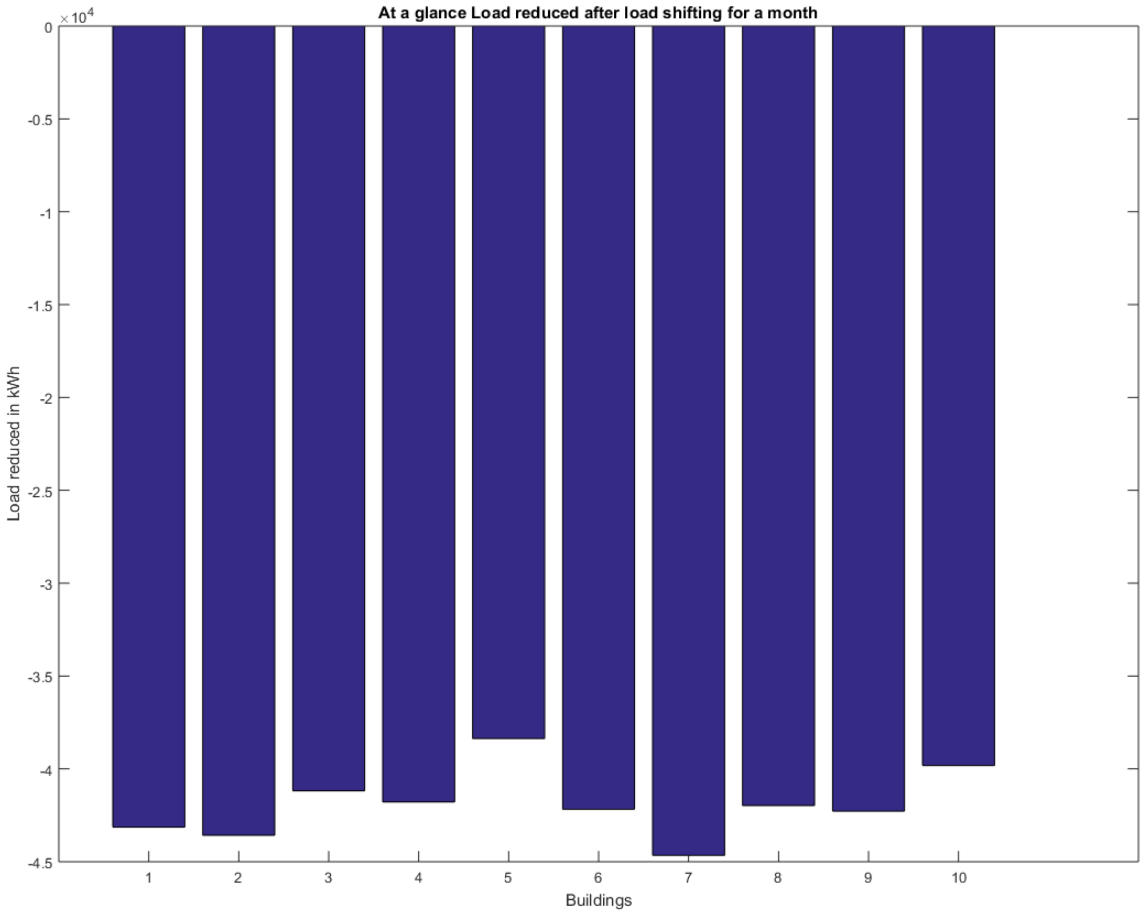


Figure 72: Load reduced after load shifting for a month

5.2.10 Monthly RT price difference in different time slots per buildings

The graphical representation in figure 138 shows that the price increased or decreased with regard to the flat-rate price. Once the RT price is applied to the PCU, then that recalculates and shows the differences in different time slots per building.

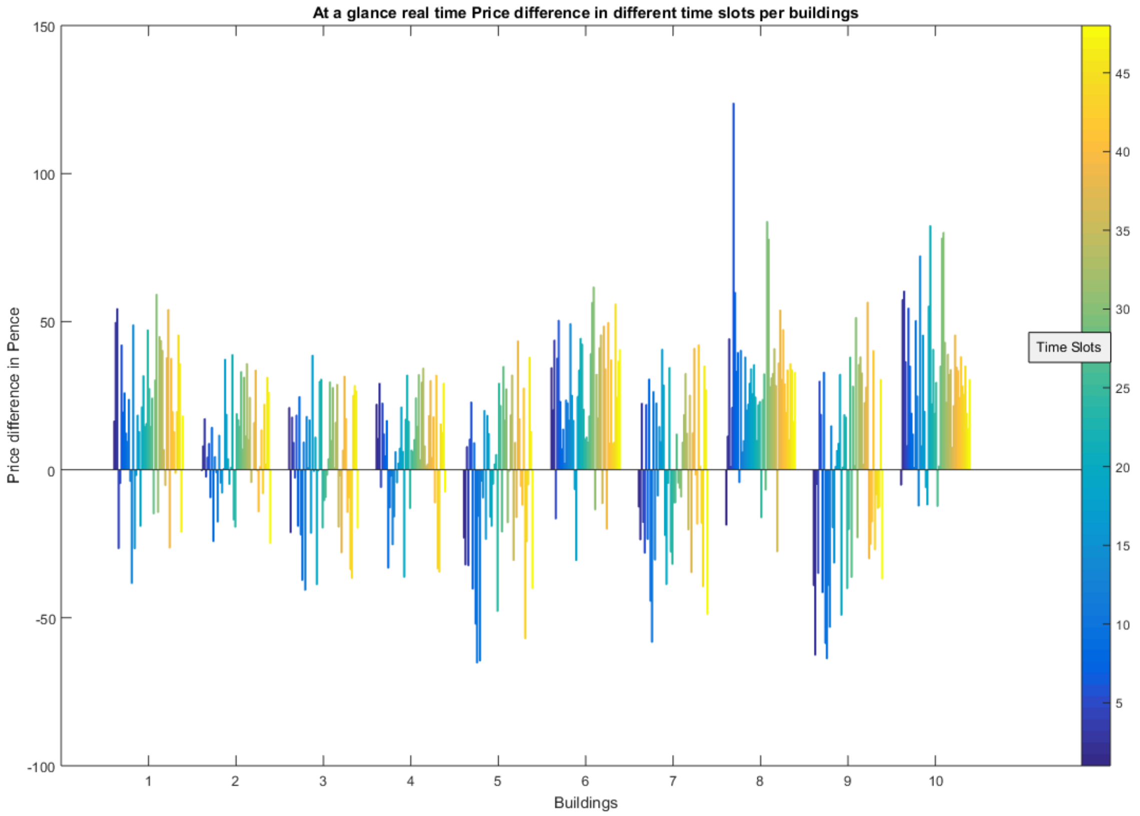


Figure 73: Real-time price difference in different time slots per building

5.3 Energy Users' real-time price savings

There are two aspects of savings: one is from the users' perspective, the other is from the EP's perspective. Users can save on their energy bill without shifting their load regarding flat-rate pricing. However, after load shifting, they can save more. After load shifting there is the significant scenario we can see: the peak load is low, henceforth, Peak-to-Average Ratio (PAR) would be less. The EP supplies energy based on peak load. Once the PAR is reduced then they can benefit from significant cost savings. If all the energy providers use this algorithm, then overall generation would be less. This demonstrates that the overall SG benefits from the algorithm we have produced. The graphical representation in figure 139 shows the number of buildings on the X-axis and price savings on the Y-axis.

All buildings experience cost savings. We counted only 20% responses from the users once the PSU generates the load shifting signals to the users. It is a real-time half-hourly basis load shifting suggestion for which that the PSU generates signals. Figure 139 shows only one-day saving from the user perspective. We have checked the price they are supposed to pay regarding a flat rate that is reduced significantly by this real-time basis algorithm. Some of the buildings are large: the long bar represents those buildings' savings.

5.3.1 Daily RT price savings for the DfE without considering users' response

The graphical representation (figure 139) shows how the buildings reduced their bill after running the simultaneous perturbation stochastic approximation (SPSA) method. The Sanctuary building has high usages, and it gains almost 6.4%, St Pauls Place is a medium size building those gains are almost 5.5%, Castle View House and Mowden Hall have small usages. However, Castle View House gains something, but Mowden Hall lost an insignificant percentage because of their high Peak-to-Average Ratio (PAR). Our target Peak-to-Average Ratio (PAR) is 2%, Mowden Hall has 4%. We need to encourage them to reduce PAR and reduce their energy bill.

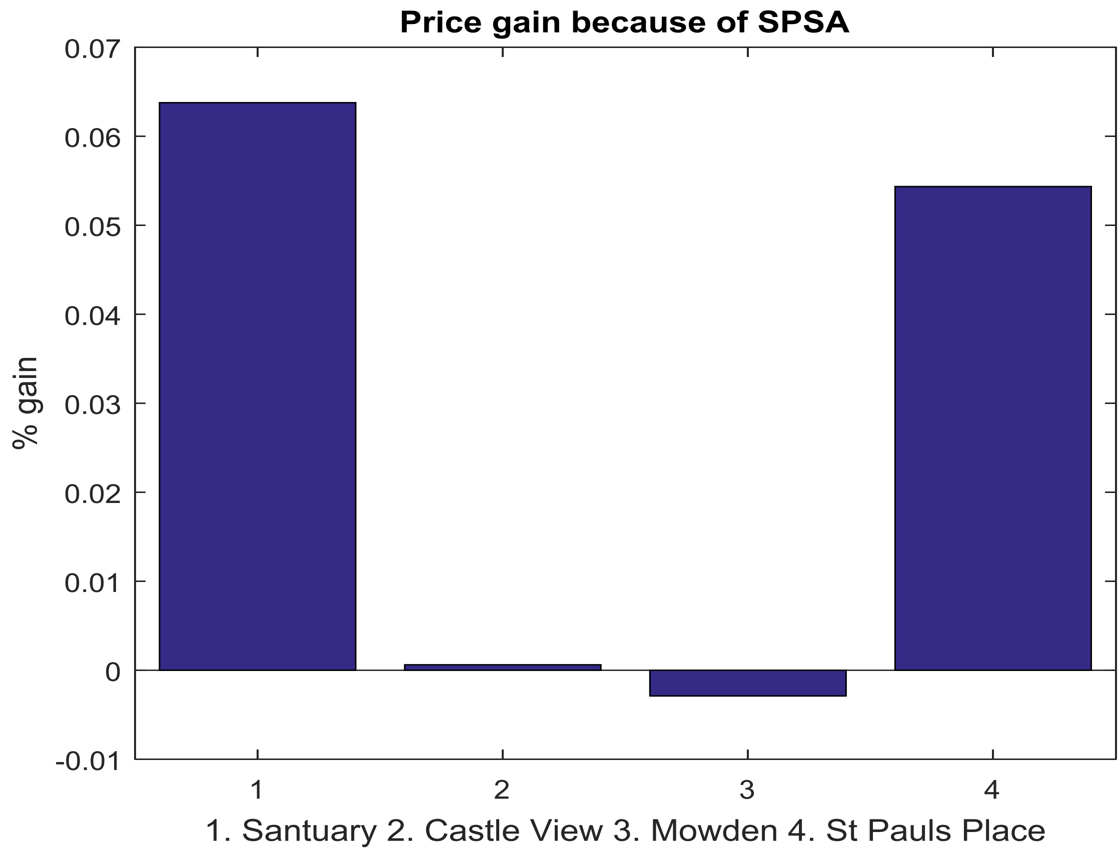


Figure 74: **Bill savings in different DfE buildings before load shifting**

5.3.2 Daily RT price savings for all DfE and UoB buildings without considering users' response

We have calculated the daily base per building real-time price savings before load shavings in the DfE and UoB buildings. This graphical representation in figure 140 shows that all 14, four buildings of the DfE and ten buildings of the UoB, reduce their bill after real-time pricing is implemented. The graph shows that one building couldn't save bill as price suggestion was not integrated. However, once we use PSU, all buildings save their bill in the figure 141 below.

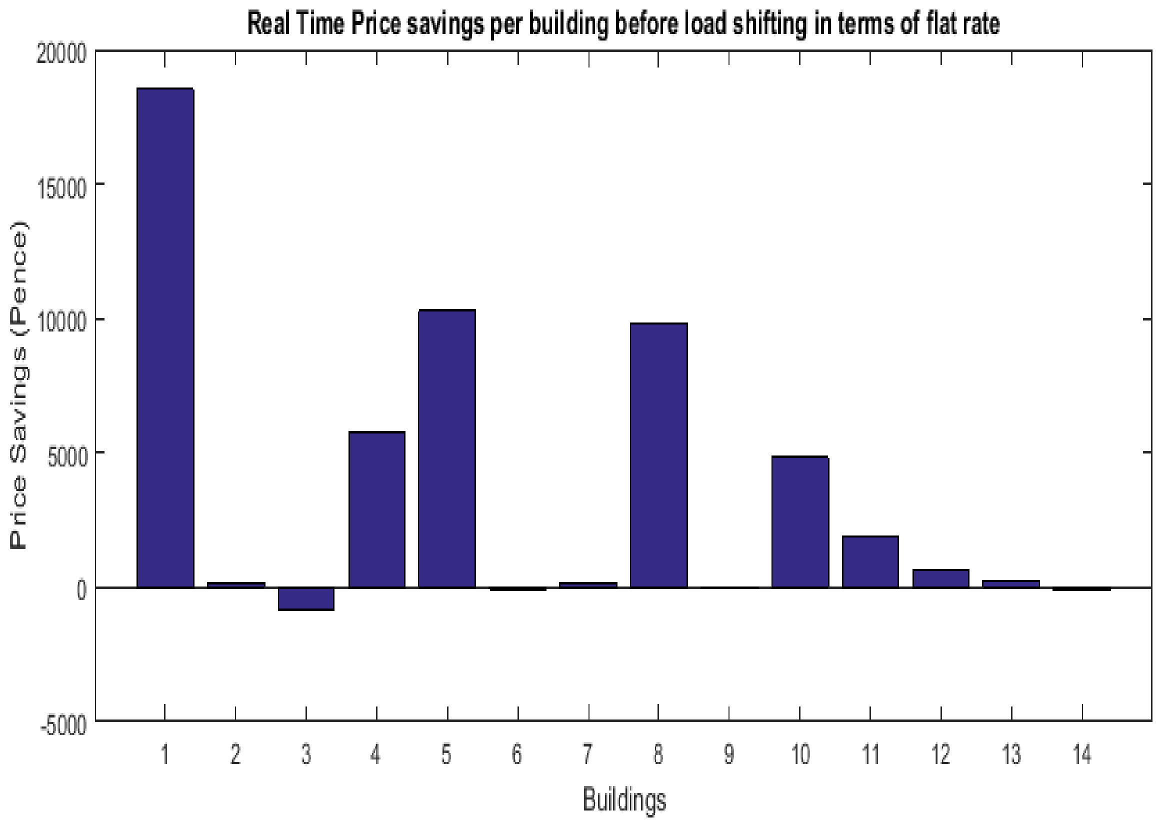


Figure 75: **Real-time price savings per building before load shifting regarding flat rate**

5.3.3 Daily RT price savings for all DfE and UoB buildings considering users' response

We have calculated the daily base per building real-time price savings after load shifting in the DfE and UoB buildings. The graphical representation in figure 141 shows that all 14, four buildings of DfE and ten buildings of the UoB reduce their bill after real-time pricing is implemented. We can see all building individually saved the bill.

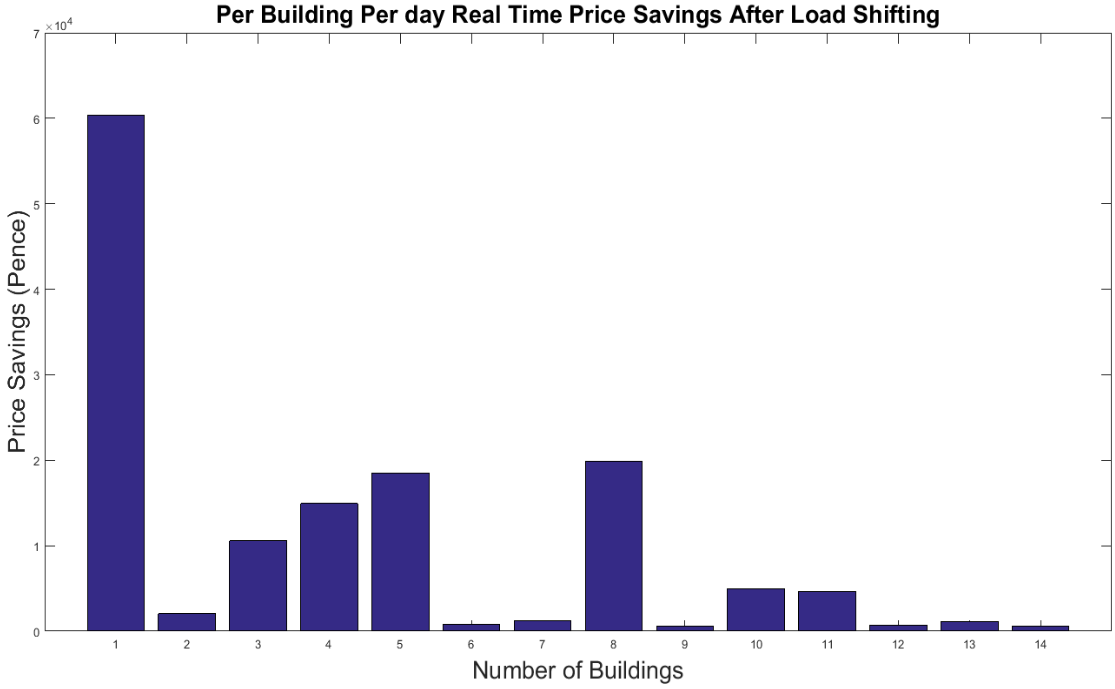


Figure 76: **Per building per day real-time price savings after load shifting**

We have checked institute base and calculated daily base per building Real-Time (RT) price savings after load shavings in the DfE and UoB buildings. The graphical representation in figure 142 shows that all 14, four buildings of DfE and ten buildings of University of Bedfordshire (UoB) save their bill after real-time price implemented.

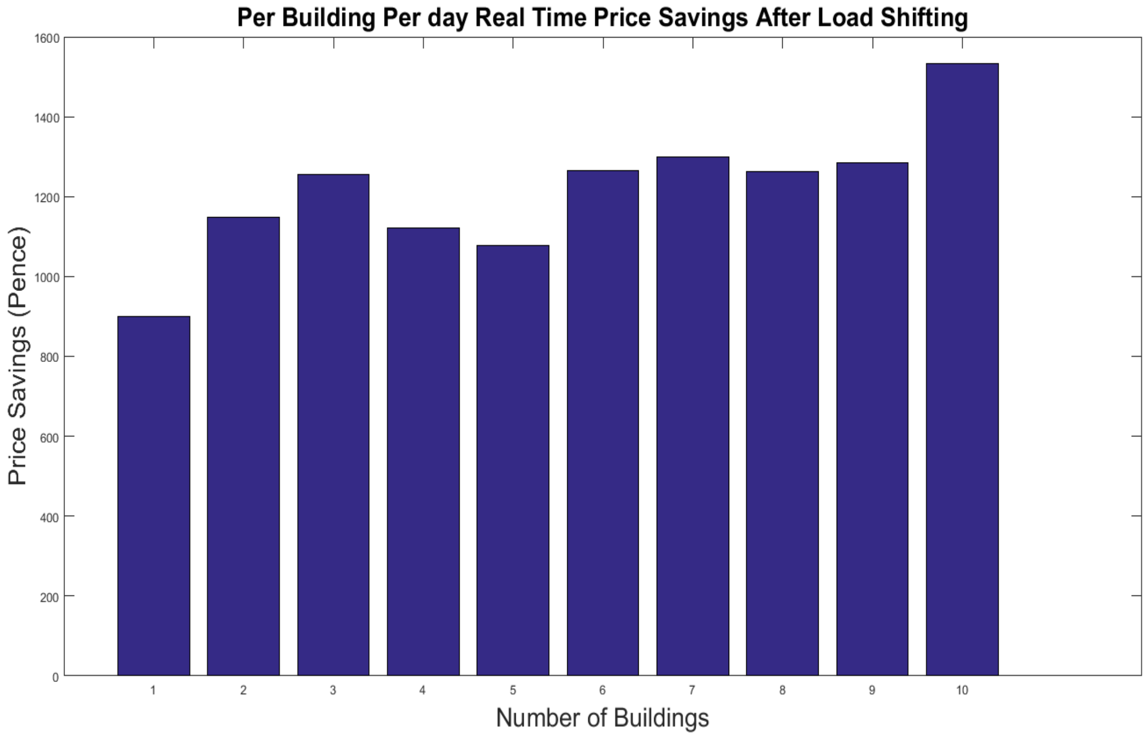


Figure 77: Per building per day real-time standardised price savings after load shifting

5.3.4 Monthly RT price savings (Std) without considering users' response

We have calculated the monthly base per building real-time price savings before load shifting in the DfE and UoB buildings. The graphical representation in figure 143 shows that all ten buildings of the UoB reduce their bill after real-time pricing is implemented. We used 30 days' data of UoB only because we did not find the similar month of data from DfE buildings.

Figure 78: Monthly RT price savings (std) compared to flat rate before load shifting

5.3.5 Monthly RT price savings compared to flat-rate price considering users' response

The graphical representation in figure 144 shows how the buildings reduced their bill based on their capacity, but figure 143 shows the standard savings without considering the capacity of the buildings as small or large. The figure 144 shows that every building save their bill in terms of flat rate once they use PSU which helps a huge savings for them.

Figure 79: **Monthly RT price reduction compared to flat-rate price after load shifting**

5.4 Peak-to-Average Ratio (PAR) analysis

Most importantly, energy suppliers are not losing money, as energy suppliers' cost currently depends upon 'peakers'. Peak load leads to their industrial cost. Our model addresses that issue. The model can assist in reducing the Peak-to-Average Ratio (PAR) from 1.5 to 1.1. As we mentioned earlier, considering only 20% random responses to load shifting, the energy suppliers are better off. Our model assists to reduce PAR after load shifting. If all energy suppliers are using this model, the power plant does not need to generate so much energy to meet the users' electricity demand. Figure 144 showed that after the load shifting real-time price reduction, none of the users is overcharged compared to the flat-rate bill. Everyone is better off with the real-time pricing.

The overall peak demand in DfE buildings before load shifting is 1716 kWh, once the 20% response from the users is counted, peak demand is reduced to 1587 kWh after the load shifting. Peak-to-Average Ratio (PAR) before load shifting is 1.52 and Peak-to-Average Ratio (PAR) after load shifting is reduced to 1.34. Average demand overall from users before load shifting is 1178 kWh, average demand overall from users after load shifting is 1127 kWh. Overall total energy load is reduced after load shifting to

2447 kWh. The calculation is made on overall Peak-to-Average Ratio (PAR) based on buildings' total loads from the EP's point of view. The EP would think about the total load demand from energy users. Nonetheless, whatever demand is in particular a time slot out of 48 slots, the EP supplies same amount of energy to meet the demand of energy users. To meet the users' peak demand, the EP supply highest amount of energy. We calculated what would be the ratio of peak demand and average load as Peak-to-Average Ratio (PAR).

We also calculated individual building's base PAR, so that we know the individual building's PAR. Based on overall average energy consumption, we assume that at least we could bring down the peak load to the average load. We define it as targeted PAR. However, we calculated PAR before and after the price suggestions, which brings the excellent results that have been shown in figures 151 and 152. It shows users' costs are influenced by the peak energy consumption that is found, which can be suggested to reduce to average consumption, i.e. users would shift their load from the particular peak time slot to another slot that demonstrates below average consumption. Real-time pricing has been calculated by using a simultaneous perturbation stochastic approximation method that reduced users' bill significantly, which we have discussed in the previous chapter. To address the reduction of PAR, SPSA would manage to reduce users' bill based on their usages, but it would reduce this more if we consider adding users' responsiveness, which has been discussed with the previous graphical representations.

5.4.1 Daily DfE Peak-to-Average Ratio (PAR) without considering users' response

This graphical representation in figure 145 shows that all buildings have an average 1.6% of Peak-to-Average Ratio (PAR) except Mowden Hall, the overall Peak-to-Average Ratio (PAR) is 1.5%, too. However, our target PAR should be 1.6% by considering the average load 678 kWh per time slot out of 48 time slots. Our objective is to minimise into 1.6%. The Sanctuary building has 1.6 %, Castle View House has 1.4%, Mowden Hall has 1.9%, and St Pauls Place has 1.4%.

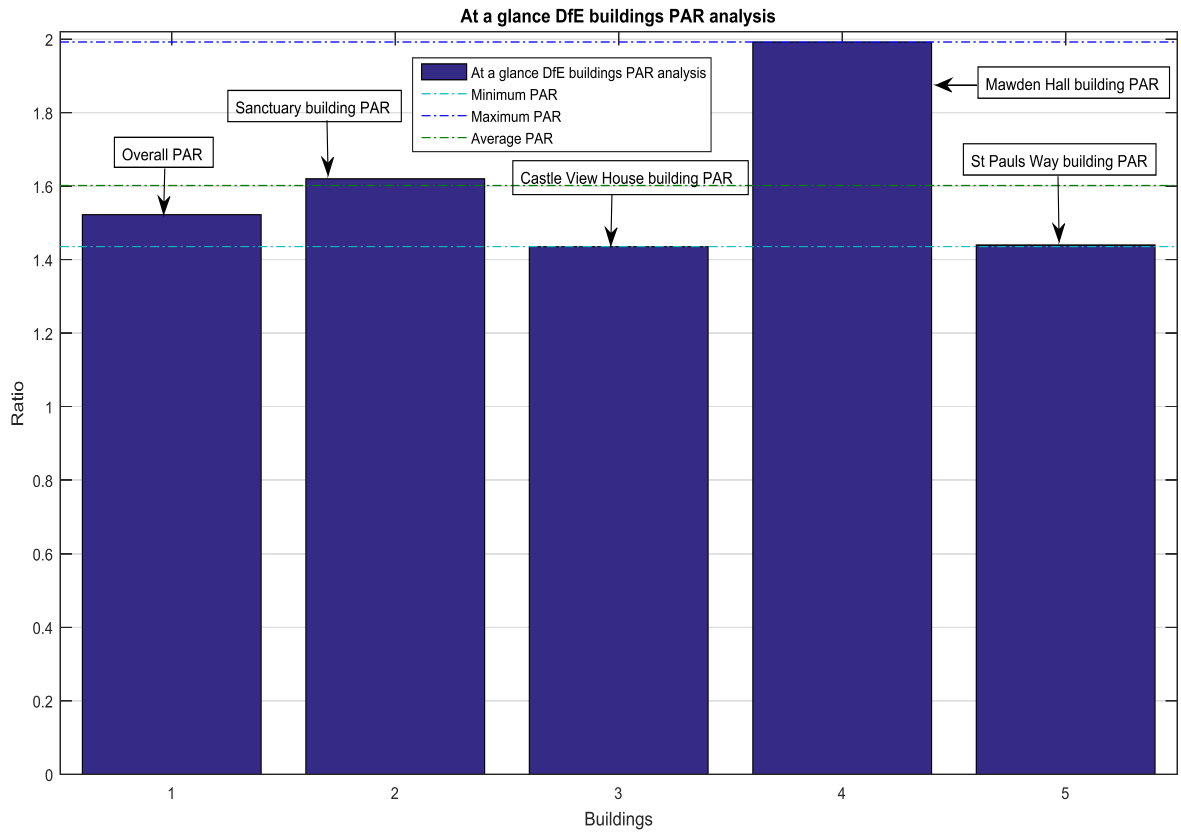


Figure 80: Peak-to-Average Ratio (PAR) in different DfE buildings compared to overall

5.4.2 Daily UoB Peak-to-Average Ratio (PAR) without considering users' response

We have calculated in the UoB buildings with overall PAR. We have found PAR Overall is 1.5%, PAR Campus is 1.8%, PAR Johnson is 1.9%, PAR Lidle is 1.5%, PAR Paget is 2.0%, PAR LRC is 1.4%, PAR Park Square is 1.1%, PAR Putteridge Bury is 1.6%, PAR Scott is 1.3%, PAR Stainier is 1.5%, PAR Stephenson is 1.7%. This graphical representation in figure 146 shows that minimum, maximum and average PAR based on their minimum, peak and average load consumption.

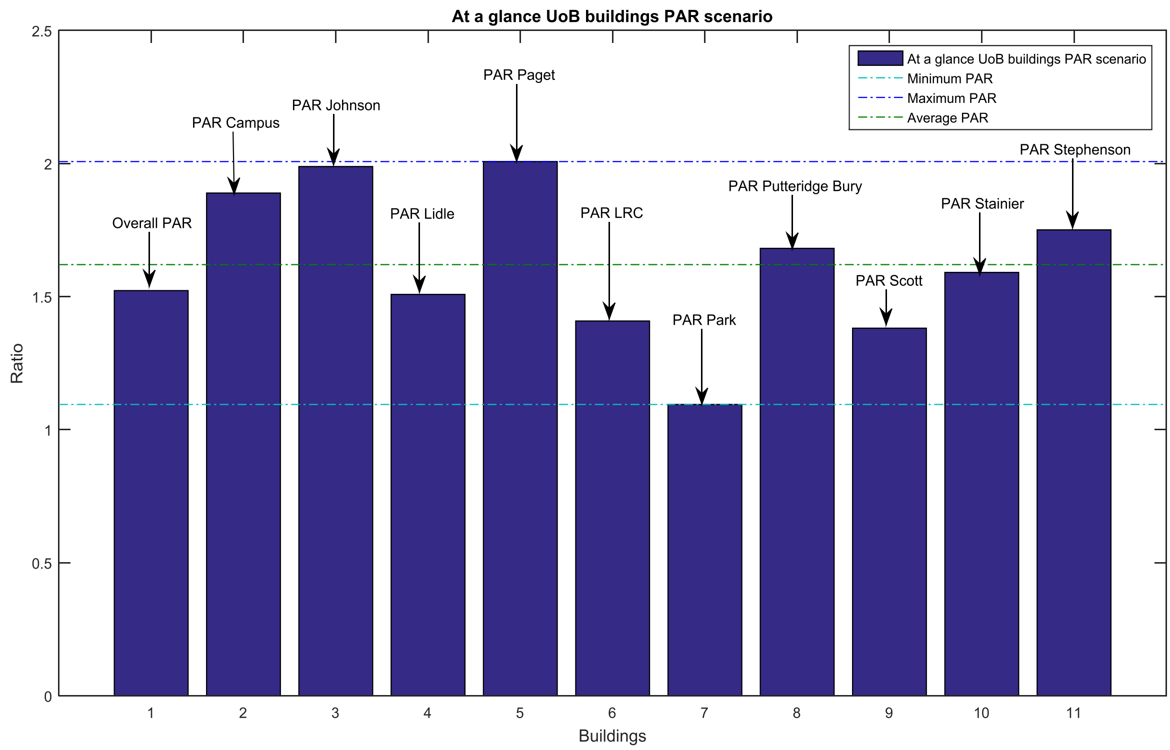


Figure 81: **UoB buildings' PAR scenario**

5.4.3 Daily UoB Peak-to-Average Ratio (PAR) considering users' response

The graphical representation in figure 147 shows that the daily basis Peak-to-Average Ratio (PAR) of different UoB buildings, the highest PAR is nearly 1.6% and before load shifting actual PAR 1.5% has been reduced to 1.3% once load shifted after receiving the responses from the users.

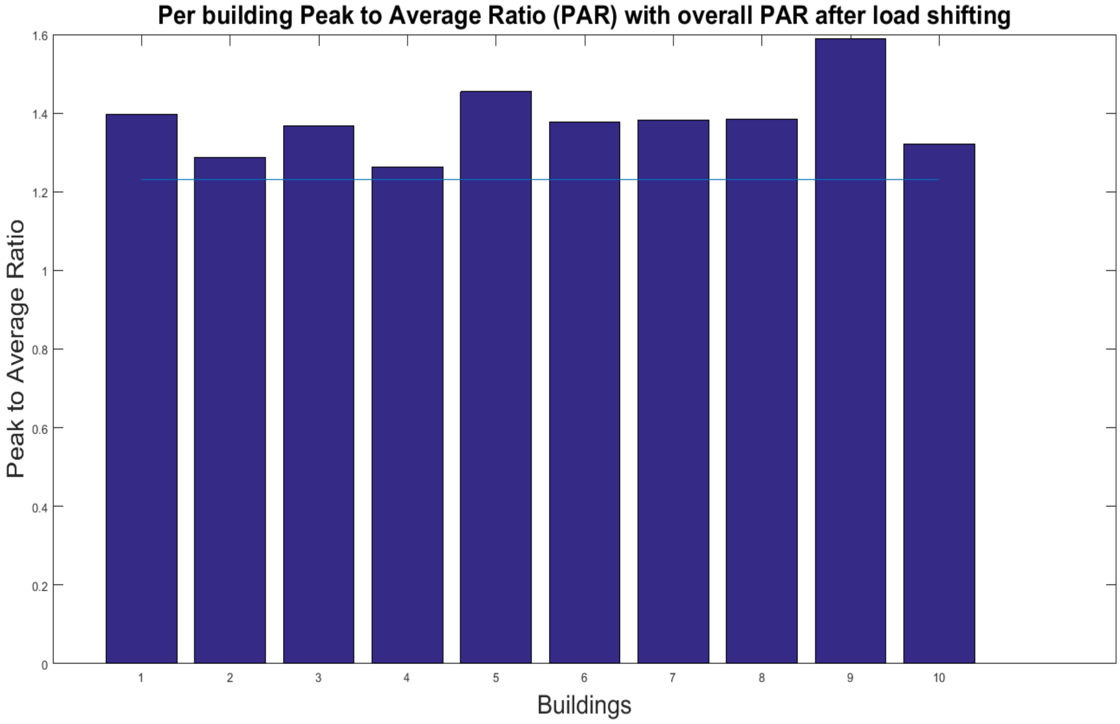


Figure 82: Per building PAR with overall PAR after load shifting in UoB

5.4.4 Daily overall PAR without considering users' response in the Smart Grid

The graphical presentation in figure 148 shows that ideally, all buildings should have 1.52 PAR. Each different building has a different level of PAR regarding their average consumption. Figure 148 shows that overall all buildings managed to reduce their PAR. In terms of ideal PAR, this figure shows different buildings' PAR. It is significant to know that considering both institutes separately figure 145 and 146 shows that overall PAR in the SG would be almost 1.5. We have checked combine, it is also the same as 1.5. Our target is to reduce it in the Smart Grid. Our model reduced that overall PAR significantly and it reduced to 1.3 and it shows in the figure 150. Energy provider is always very desperate to reduce the PAR, as it relates to their cost paying to the main power plant. This significant result shows that model benefit the energy supplier and we have shown in the previous discussion how every bill payer saved their bills.

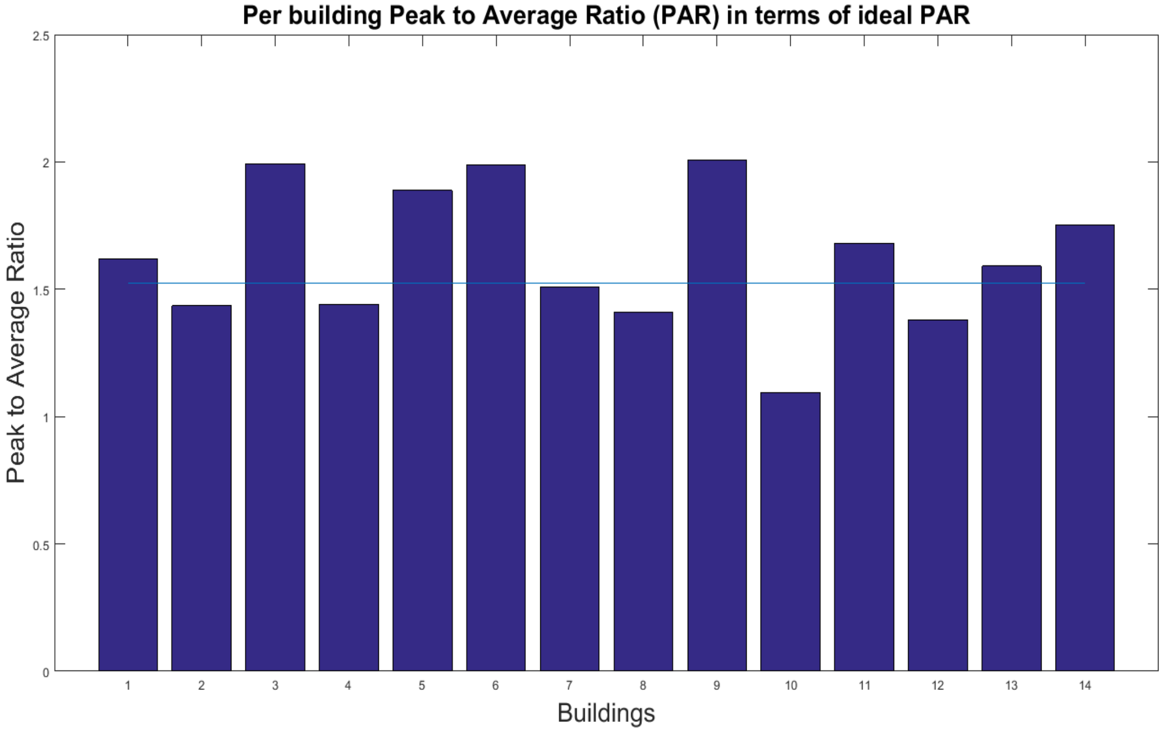


Figure 83: **Per building Peak-to-Average (PAR) regarding ideal PAR**

However, after load shifting different buildings achieved a different level of reduced PAR and overall they managed to reduce from 1.52 to 1.34 (in figure 150). The graphical representation in figure 149 shows all buildings reduced their PAR. In figure 149 (Appendices), it shows that PAR scenario without using price suggestions.

5.4.5 Daily overall PAR considering users' responses in the Smart Grid

Considering the daily basis of all building loads, we calculated PAR after receiving the response from users. It shows that the system manages to reduce the PAR, which is our desired PAR. Figure 150 show that daily basis PAR has been reduced from 1.53 to 1.3. Overall PAR in the SG was 1.53 which has been shown in Figure 148.

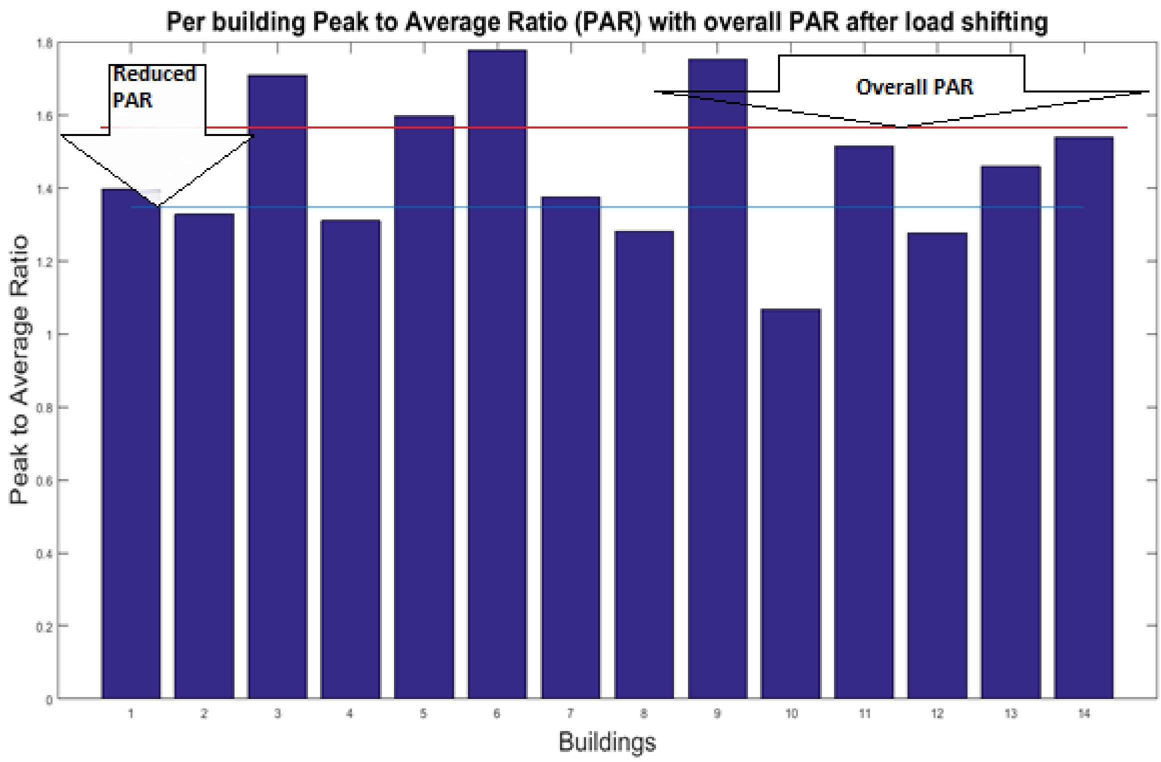


Figure 84: Per building PAR with overall PAR after load shifting

5.5 Validation of the RTPS model with hardware

We have designed an electrical circuit board which has the option to connect light bulbs and others appliances with power extension cables. Once those appliances are connected to the Arduino board, it starts reading analogue data through pin A0. The sensor is connected to the direct current and the Arduino board.

A MATLAB program was configured with Arduino add-on hardware support packages. Once it is connected, it reads live data from various appliances' energy consumptions. It converts into the actual kWh to fit into our algorithm. It makes suggestions and calculates users' prices and reduces the overall Peak-to-Average Ratio (PAR) for the energy providers.

We have tested with one user from Arduino and another one from our real university building data in order to make multiple users. There is an option to accumulate more users and test with a live data connection to generate required values for our algorithm.

We have also tested with a Raspberry Pi as a webserver where we can collect and store the data generated price suggestions. We calculate the real-time reduced price with our stochastic approximation algorithm; also we can display data in the Raspberry Pi and make it interactive to users.

We have tested making the Raspberry Pi as an FTP server which is connected to the PC as the Raspberry Pi is sometimes not good enough to carry on the loads because of having less memory. In all aspect, it is possible to make a price suggestion unit which is our novel contribution to this thesis. Figure 151 shows our circuit to play around with our model.

Figure 85: System test with Arduino

5.5.1 How a commercial system would be designed

We can collect live electricity usages with each Arduino as an energy user. With multiple EUs connected to the Raspberry Pi with a display unit, we can make it interactive. We can generate price suggestions in the display unit. We can make a website and keep it on the webserver in the Raspberry Pi. We can make mobile apps which would communicate with the webserver to make an interactive live system. This is the prototype price suggestion unit, which is our novel contribution. This can be the quickest way of testing the system as smart meters, and other equipment would be costly.

We tested the model with one Arduino with multiple appliances with our algorithm. This concept, in figure 152, would be the ideal quickest solution to further test our model. However, within the time frame of the study, this is beyond the scope of the completion of the research.

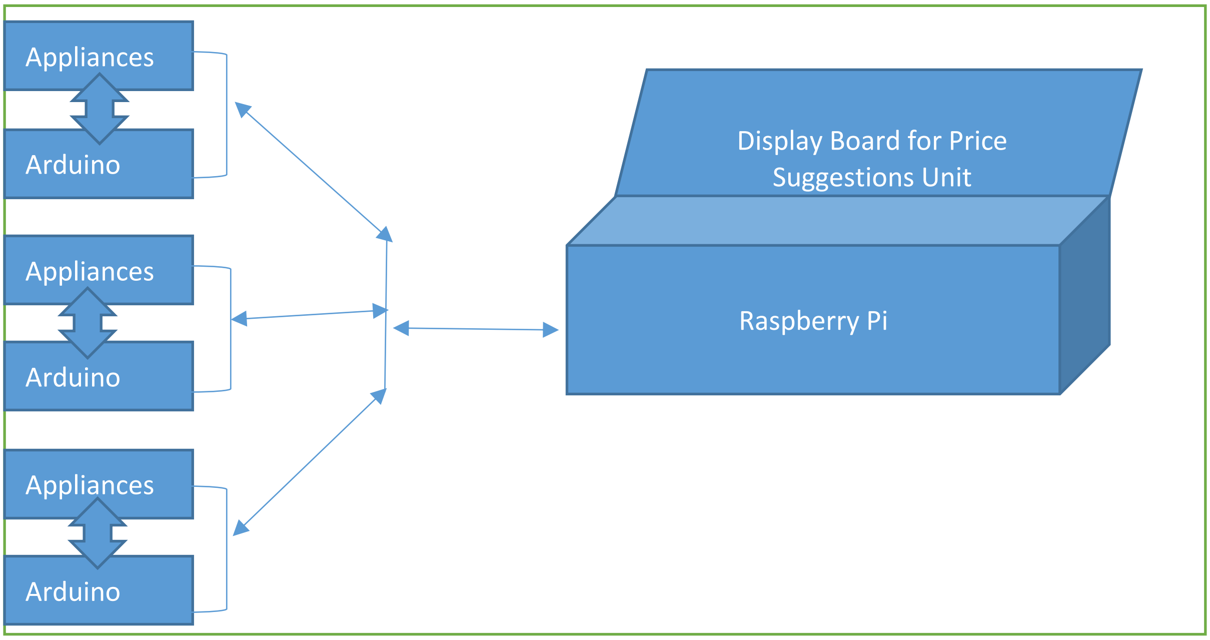


Figure 86: Prototype price suggestion unit

5.6 Interoperability

In the market, there are a number of smart meters available to communicate with the price control unit; it is a matter of communication, technology has improved to communicate with millions of customers and to receive data from users and generate the required values for users. It is beyond the scope for this research to check the viability of the communication aspects. Currently, energy providers communicate with users through smart meters as a two-way communication. The research is selected as the bi-directional communication is established already; there might need to be improvements, which is another dimension of the research. Seamless data exchange rate within the SG communication is vital. Compatibility through open standards is significant in the DR operational perspective. It ensures [163] the overall system is unresponsive to adjusting any basic components.

Our novel contributed model is part of the market-based approach. As per our investigation, smart meters are in the market, which we have explained in our literature review. The price control unit is also an available concept in other research. There are some challenges which have discussed in the discussion on security and interoperability challenges section. One research work [164] addresses interoperability: the NAESB (North American Energy Standards Board) explained in PAP10 – the Energy Usage Information (EUI) Model to ensure interoperability. We can fine tune the RTPS model on this issue.

5.7 Quality of Service (QoS)

QoS is important for a DR programme; however, it is necessary for communication with the SG. The reliable transition of data in an emergency response is also a significant phenomenon. Bandwidth is required for smooth price signal generation. Furthermore, communication infrastructure should provide adequate bandwidth with minimum latencies regarding ensuring the QoS. Real-time sensing in a pricing system can be reached in a few milliseconds [165]. However, our model is simulated in the laboratory for the research purpose and in the real-life scenario communication infrastructure would already be developed, which would be enough to ensure QoS. However, ensuring the communication mechanism is beyond the scope of the research time frame.

5.8 Scalability and flexibility

A large number of electricity users' participation in the DR pricing programme with adjustable load are obtainable for flexible demand [166]. Consequently, a highly scalable communication infrastructure is important for adaptation with a huge number of devices. To the contrary, flexibility allows an alternative way of data transition. A cloud-based solution leverages scalable data communication between the EP and users [167]. Therefore, our model would work with the flexible demand with a large dataset. The methods we have used have been implemented in various disciplines. However, there may be room for fine-tuning the algorithm if necessary once we use the algorithm with the large dataset, for example with a dataset of millions of customers' energy usage. We may extend this part in a later stage.

5.9 Security

Security is a crucial factor in the SG, particularly in the operational network infrastructure. It maintains data authentication, confidentiality and integrity in non-denial services [159]. Any meddling information may prompt financial and legal problems, like malware infecting the SG and damaging the data. Therefore, absolute security is necessary for the SG DR programme. It is also important to keep users' private data intact. Preventing unauthorised data access and averting corrupt information from the communication mechanism are vital, as well. However, our model would follow the standard communication mechanism which is built into the Smart Communication Grid.

5.10 Web-based architecture

There are a number of web-based architectures available. A number of technologies explored in one research paper [168] shows that Zigbee/IEEE 802.15.4 would be a better communication technology for power efficiency, accordingly web-based architecture is presented in the findings.

There is a number of research works that have been carried out such as one paper that addresses a home gateway which constructs interoperability among different devices: one of them [169] used sensors to monitor the energy. In another paper [170] discusses the RESTful interface for building an energy management system with bandwidth limitation of WSN (Wireless Sensor Network).

Sensor-Actuator Gateway Agent (SAGA) [171] has easy operation through a web interface. There are two familiar web services technologies: one is SOAP (Simple Object Access Protocol) and another is REST (Representational State Transfer). Our model can be placed in the user interface to interact with energy users. It is possible to develop a web portal and mobile apps through which users can control their bill by implementing the price suggestions.

5.11 Variation and validation

5.11.1 Variation of electricity usages data (sample)

This graphical representation shows that all DfE offices are in normal operation mode and all offices are in operation 24 hours a day. Figure 153 shows that employees worked all the way from 12 am to 12 pm in a similar way with different amounts of variation of electricity. Overall, maximum consumption of those four offices was 731 kWh and minimum consumption was 18.3 KWh, and average consumption was 219.9 kWh. Building base minimum, maximum, average consumption are given in the table in figure 154. The graphical representation shows energy consumption in different buildings.

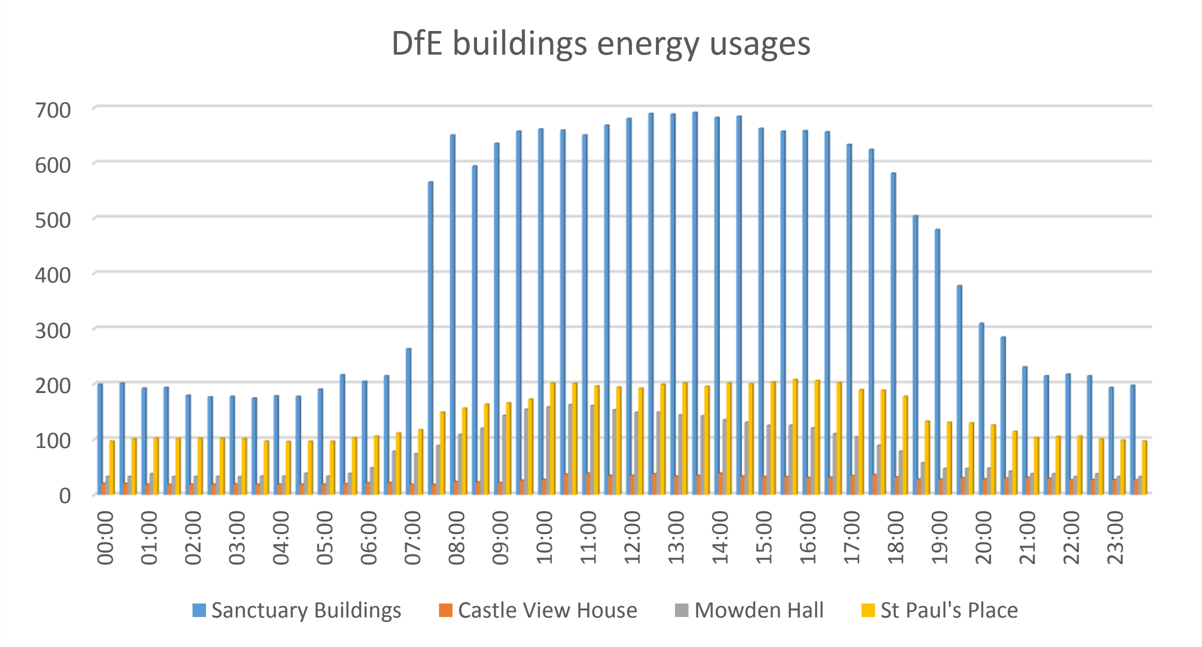


Figure 87: Graphical representation of four offices' energy consumption

This table in figure 154 shows these four office (sample) buildings' maximum, minimum and average consumption distribution. Hence, we can see the variability of the buildings is very significant: some of the buildings are small, medium or large. Our model handles that variability.

Offices	Maximum	Minimum	Average	Total	Level
Sanctuary building	691	174	426.6	20475.0	Large
Castle View House	38.6	18.4	26.9	1290.8	Small
Mowden Hall	162.1	32.4	81.4	3906.0	Small
St Paul's Place	207.4	95.6	144.1	6915.8	Medium

Figure 88: Four offices' maximum, minimum and average energy consumption

5.11.2 Validation of data

By using the Principal Component Analysis (PCA) algorithm, we can compute a 48 slots basis maximum, minimum, mean and standard deviation in each slot for four different buildings. If we consider the four buildings together, the statistics show in the figure 155 that the data disperse a lot with high standard deviation because one is large, one medium and two are small buildings; accordingly, their energy consumptions are varied. The PCA algorithm has analysed 30 days’ data. In conclusion, data variability is high. However, the stochastic nature of the algorithms can handle the data. Our model successfully fit the data. We are going to conclude the thesis in the Chapter 6 below.

Variable	Minimum	Maximum	Mean	Std. deviation
Slot1	15.100	240.000	84.916	70.628
Slot2	15.400	244.000	85.463	70.406
Slot3	15.400	229.000	83.367	66.955
Slot4	15.500	226.000	82.415	65.487
Slot5	15.100	225.000	81.944	64.811
Slot6	15.400	228.000	81.805	64.963
Slot7	15.400	215.000	81.785	64.250
Slot8	15.500	221.000	81.083	64.379
Slot9	15.500	216.000	81.508	65.238
Slot10	15.900	226.000	83.040	66.734
Slot11	15.500	244.000	85.963	70.471
Slot12	15.700	259.000	91.799	77.002
Slot13	15.800	260.000	93.756	78.356
Slot14	13.800	274.000	102.011	78.663
Slot15	12.300	314.000	108.356	92.743
Slot16	12.400	676.000	164.806	189.551
Slot17	12.100	652.000	177.776	208.678
Slot18	11.800	610.000	174.973	192.843
Slot19	12.000	651.000	186.406	202.731
Slot20	11.600	685.000	195.169	210.888
Slot21	12.100	695.000	199.573	215.935
Slot22	12.200	692.000	199.829	214.476
Slot23	11.700	700.000	200.198	216.400
Slot24	11.800	714.000	201.353	221.599
Slot25	12.000	719.000	201.769	223.342
Slot26	12.000	719.000	201.464	223.677
Slot27	11.700	720.000	201.597	224.685
Slot28	12.300	723.000	201.551	225.422
Slot29	12.600	721.000	200.778	225.446
Slot30	12.400	712.000	198.245	222.622
Slot31	12.400	731.000	197.072	221.580
Slot32	12.600	712.000	195.022	218.941
Slot33	12.200	692.000	192.206	217.342
Slot34	12.600	685.000	188.253	215.232
Slot35	12.200	680.000	183.953	211.422
Slot36	12.300	663.000	178.233	206.783
Slot37	12.300	618.000	167.427	190.159
Slot38	12.200	521.000	144.535	164.291
Slot39	12.100	489.000	138.455	156.550
Slot40	12.200	399.000	120.696	122.631
Slot41	11.900	321.000	106.540	98.446
Slot42	12.800	298.000	100.172	91.260
Slot43	14.100	277.000	95.273	83.908
Slot44	14.800	268.000	92.015	79.916
Slot45	15.200	245.000	89.322	75.342
Slot46	15.800	253.000	86.839	72.022
Slot47	15.500	241.000	83.949	69.122
Slot48	15.200	242.000	84.603	70.455

Figure 89: Variability of data in the 48 different slots

5.12 Explanation of the core part of the Matlab code

This is a core part of the algorithms. Simultaneous Perturbation Stochastic Approximation (SPSA) method has been applied on the basis of energy scenario as it plays vital role on multivariate stochastic optimisation. There are variables like *I, c, alpha, gamma* declared. It has been selected from the guidance from spall [137]. It can be read from another file as well. Another external file loss function to acquire the noisy quantity and that can be called from another file. Maximum and minimum value can be calculated from theta. The core part of the code is below.

```
For k=1:n
sigma_k=sigma/(k+A)^alpha;
ck=c/k^gamma;
delta=2*round(rand(t,1))-1;
Pt_R2plus=Pt_R2+ck*delta';
Pt_R2minus=Pt_R2-ck*delta';
yplus_R2=loss(Pt_R2plus);
yminus_R2=loss(Pt_R2minus);
ghat=(yplus_R2-yminus_R2)./(2*ck*delta');
Pt_R2=Pt_R2-sigma_k*ghat;
End
```

Main difficult part is ghat approximation. We need to generate SPSA to the unknown ghat. It has been explained in the chapter 4. We generate two measurement of the objective function despite different dimension of the optimisation problem. We have to guess non-negative coefficients. Choice of gain sequence is also crucial for SPSA. Rest of the implementation kept in the appendices sections. Codes are copied from the different files.

5.13 Discussion of network constraints

The compactness of the demand and distance of the circuit may impact on the network loss [172]. The rural area may have very low 0.05 MW/km^2 but the urban area may have 137 MW/km^2 peak demand density. High network operation may cause network loss in urban area but long feeder length may cause for the network losses in the rural area. However, 20% feeders may be responsible for the 70% HV and 50% LV network losses. From the power plant to distribution network, voltage has to be reduced and it may cause network loss, however, reduced demand during the voltage reduction may reduce the network loss. It might not be case all the time. Nonetheless, our model could not focus on considering this circumstances. Transmission loss is also an issue in the power network as peak demand determine the marginal losses. It is worth to say, 0.055 MWh loss reduction in transmission network may be generated from 1 MWh loss reduction in distribution network. Nevertheless, DSM may benefit the loss reduction. In the low loading situation, switching off the transformer may potential for overall losses reduction. In our model, we assuming that energy demand consists of continual loads. It did not focus on thermal or network losses which are primarily related with LV, HV network and transformers. The study shows [172] that “36-47% losses from LV, 9-13% from load related loss and 7-10% from no-load losses are associated with the distribution transformer. 17-27% are from HV network. 17-24% of total losses are in primary and grid transformers, and EHV and 132 kV networks.”

6 Conclusion and Future Work

This thesis has presented a novel Real-Time Price Suggestion (RTPS) Demand Response (DR) model integrated with Price Suggestion Unit (PSU) and the Price Control Unit (PCU). This model has presented the algorithms with its analysis, and how the model is of benefit to both EP and energy users. The model has been tested using MATLAB. This chapter summarises the research work and draws a summary along with a conclusion and suggestions for future work.

6.1 Summary of the rationale

As mentioned earlier, over the past few decades, technologies have experienced the development of a service model that makes our daily lives more convenient and comfortable, despite the fact that the population has more than doubled over the past century and led to an exponential growth in energy. This growth is unsustainable. Currently, the power grid is a traditional grid which is for electricity generation, transmission, distribution and control. It is a unidirectional, transmitting power from generators to customers. Most developed countries have had their electricity grid for more than 50 years, and these have become outdated.

The SG is the ultimate solution to reducing the power load, decreasing the carbon footprint and making the whole power network more reliable and secure. It is a bi-directional electricity network that can intelligently integrate the actions of all users connected to an energy grid to deliver electricity that is both sustainable and economically viable. There is a vision by 2050 for energy appliances with downloadable energy from appliance manufacturers that nobody could have imagined in the 1980s. People will be able to pull energy from appliances with integrated virtual energy aggregators.

An energy supplier traditionally charges end users who buy electricity on a peak and off-peak basis. Their preferences are also important to achieve the desired level of satisfaction. On the contrary, the EP concentrates on reducing the Peak-to-Average Ratio (PAR) as their cost depends on that as they buy their energy at that particular time with the high cost of the main power generation based on 'peakers'. Energy providers could maximise their profit by matching the demand from users on a real-time basis.

Currently, the of power grid's energy production almost 70% is wasted. There is a significant difference between the average and peak demand. Energy providers must, therefore, produce energy to meet the peak demand, not average demand. The unidirectional flow of energy leads to a significant challenge related to generating a system that can provide a balance between energy demand and supply. Pricing decision making is not straightforward due to dynamic pricing – it can be in centralised or distributed – it appears to have the decision made locally or centrally. We are very fortunate that we can face those challenges by using Demand Response information technology.

We discussed earlier that Demand Response (DR) is being considered as a very effective and reliable solution in the SG. It is a subset of Demand Side Management (DSM) that manages customer demand and supply based on their time shape. Reducing the aggregate load in the distribution management system and taking real-time decisions can improve the reliability of the system.

In this thesis, the proposed RTPS that takes user uncertainty, non-interaction and non-responsiveness into account. The proposed system ensures minimum energy bills for the user while optimising the profitability of the provider. Instant real-time RT price generation and suggestions with customer preferences is the most important aspect of this thesis. We have taken price control based DR mechanism into consideration. We presented a daily basis price suggestion presented in [173].

6.2 Summary of RTPS model

The Real-Time Price Suggestion (RTPS) DR model architecture where PSU would connect with smart meter to receive energy consumption signals. PSU is connected to PCU. The EP would allocate the price value in the price parameter of the PCU, then it calculates the optimised price through the pricing algorithm along with the price suggestion algorithm provided in the PSU. It generates an optimised price signal to the users by considering users' threshold consumptions. The RTPS model calculates the optimised price in each of the time slots. There are price signals in each time slot, maximum or minimum. The energy user would be charged based on their threshold energy consumption. If the user goes beyond the threshold they would be charged maximum price otherwise minimum on a real-time basis. Model generated the suggestions based on users' energy threshold consumption. He user responds to the suggestions to reduce their bill. However, if they are unresponsive still they would achieve a significant price reduction in terms of the traditional flat-rate price TOU which is in the market.

This Real-Time Price (RTP) based Demand Response model considers user preferences as well as using stochastic optimisation techniques. Considering variable pricing from both renewable and non-renewable energy sources, the proposed real-time pricing algorithm would solve the issue for the SG. We have considered 14 buildings' 48 half-hourly basis energy consumption.

There are different fundamental aspects of contributions to our model RTPS constitutes the final thesis of the PhD. The real time pricing is better than flat rate pricing, various developed daily and monthly basis algorithms in the PSU and PCU by using SPSA. We have found the time slots that can be suggested to users in order to manage their load more effectively and reduce their Peak-to-Average Ratio (PAR) through the use of a Price Suggestion Unit (PSU) that is a fundamental contribution of this research. Finally, the model has been validated by building a hardware prototype.

This model significantly reduced the energy users' bill, and energy provider's cost as the Peak-to-Average Ratio (PAR) is reduced significantly using this approach. This model benefits both energy consumers and providers. As part of the prototype we have successfully implemented the algorithm in the Price Control Unit (PCU) and Price

Suggestion Unit (PSU) and generated results as explained in Chapter 5 (experiment and analysis).

6.3 Summary of the result

We can see from the result produced in the experimental Chapter 5 that users' reduced their bills following the price suggestions. By using users' preferences, this model leads to a potential price saving. After following the price suggestions, every building can efficiently manage their usage and potentially save money on their bill. They used our price suggestion, all benefitted in terms of usage and cost savings. Within the model, we used, as a basis, a 20% random response rate to drive our system. The model applies price savings to all customers (where possible) even if a customer is non-responsive by considering others responses and fitting this across the entire user population.

We can conclude that users can achieve cost savings corresponding to their traditional TOU price by considering their preferences (see figures 140 and 141). Through our testing so far we have seen PAR reduced from 1.5 to 1.1. We can also conclude that an energy users' response helps more to reduce the PAR which is more desirable for the energy providers (see figures 150 and 151). We have tested our model using both a daily and monthly basis to check whether the building is efficient on a daily basis price or whether cost savings can still be achieved. The results show that the model can lead to savings even when users are non-responsive, in most cases. In contrast, all monthly based price calculations led to savings for all users and buildings.

This simulation model is based upon multiple clients and a single energy provider. On a half-hourly basis measurement is recorded and the entire time cycle of 48 half-hour time slots is used (for a single day). The power requirements might vary in each slot. The proposed model addresses the issue of cost-effectiveness by implementing a Demand Response model in the SG. Moreover, it would collect information from a local distributed system, and manage users and energy providers automatically. It could then find users' optimal consumption to reduce the aggregate load. This would also reduce production cost for energy providers and still satisfy the consumers' demands. We would suggest fine-tuning this model for future work. Many countries are investing in SG infrastructure to make it more viable. Industry can implement our model in the current state of the SG infrastructure, which we have discussed in our literature review in the Chapter 2.

To ensure real-time communication between users and energy providers, a robust, secure and reliable communication infrastructure is important for implementing Demand Response programs in the future SG and that can change the future direction of the research to support this proposed model. This approach could be achieved through exploitation of communication protocols in the market including Zigbee or the Internet of Things. Secure routing, interoperability and scalability, QoS support, effective and efficient SG are critically significant, and is an area of further work that could expand the contribution of our proposed model.

6.4 Future work

The main focus of future work is envisaged to revolve around the use of multiple energy providers to yield better-optimised prices for users, but controlling various energy sources and high penetration of renewable energy, especially how surplus energy can be dispersed and shared with all customers. Our work could be expanded by integrating multiple energy providers into the model. Our model can accommodate incentives and price based hybrid DR if necessary as it is only price base DR.

However, artificial intelligence is an additional method that can help advancement of this work. In particular, predicting half-hour usage/cost based on previous historical data to justify real-time supply, fitting a neural network or deep neural network would be the solution (in consideration with some factors like weather conditions). The current model could be extended to predict on a half-hour basis by considering five years' data (for example). Most of the research predict their day-ahead load based on previous-day data only.

Finally, we can draw a conclusion that our model would work on the industrial level. Our novel contributed model Real-Time Price Suggestions (RTPS) integrated with Simultaneous Perturbation Stochastic Approximation (SPSA) methods successfully manage to make a suggestion for the users. It reduces the energy bill of the energy users significantly and the cost of the EP by reducing the Peak-to-Average Ratio (PAR) in the Smart Grid.

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7 Appendices

7.1 Different figures for references

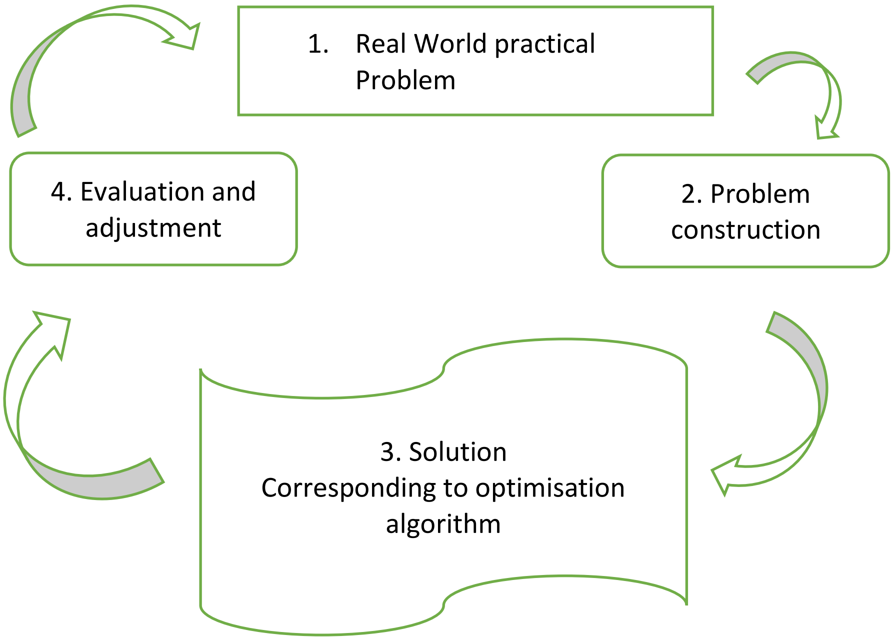

Figure 90: Algorithm working process (in general) in the real world

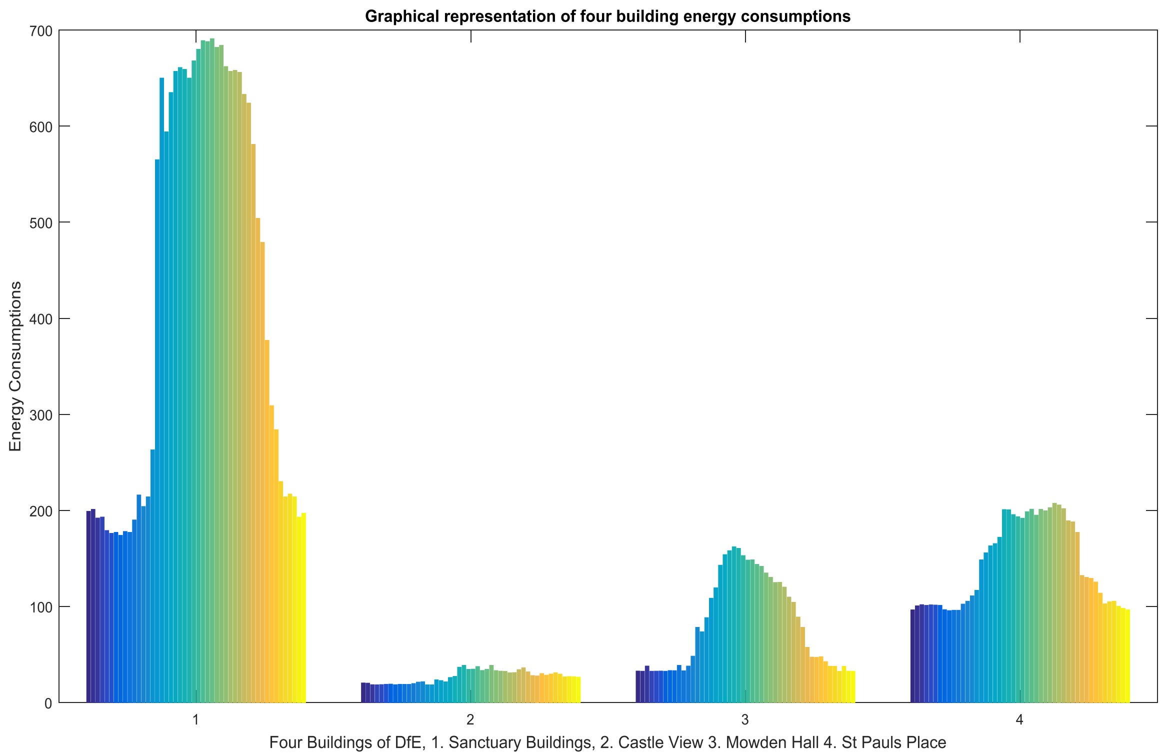

Figure 91: Load distribution in four different DfE buildings in different time slots

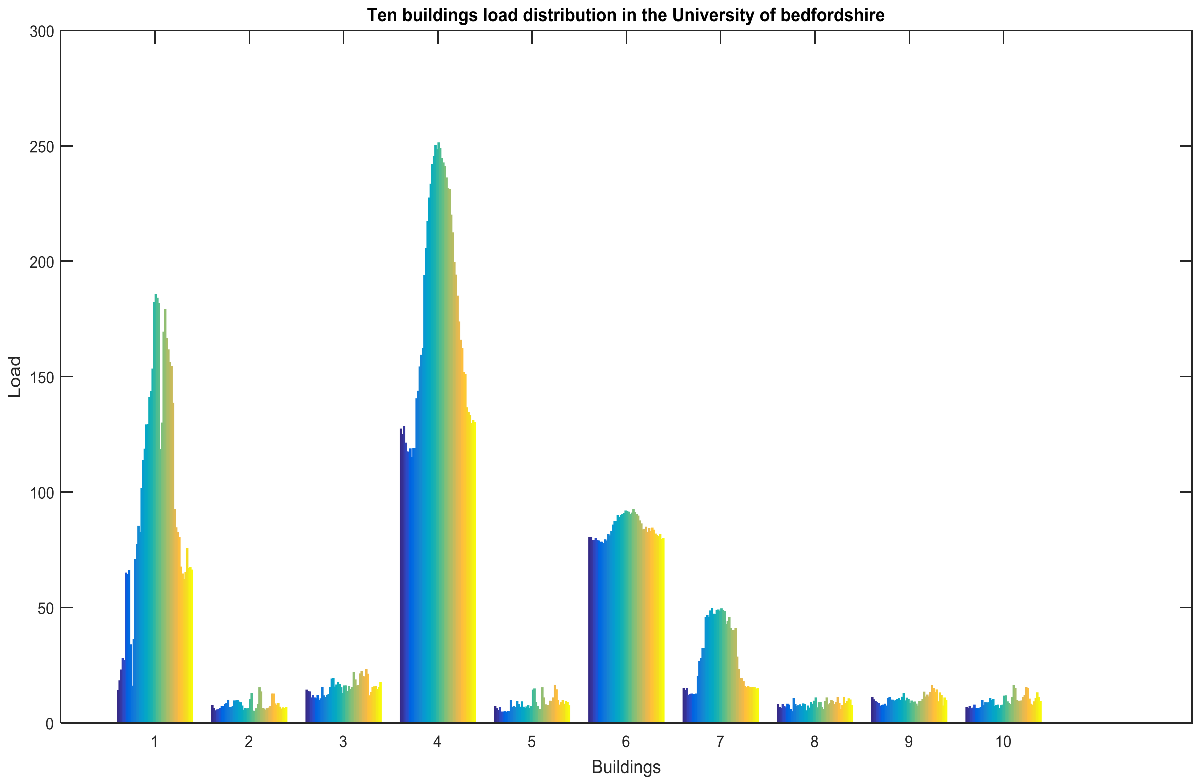

Figure 92: Load distribution in ten different UoB buildings in different time slots

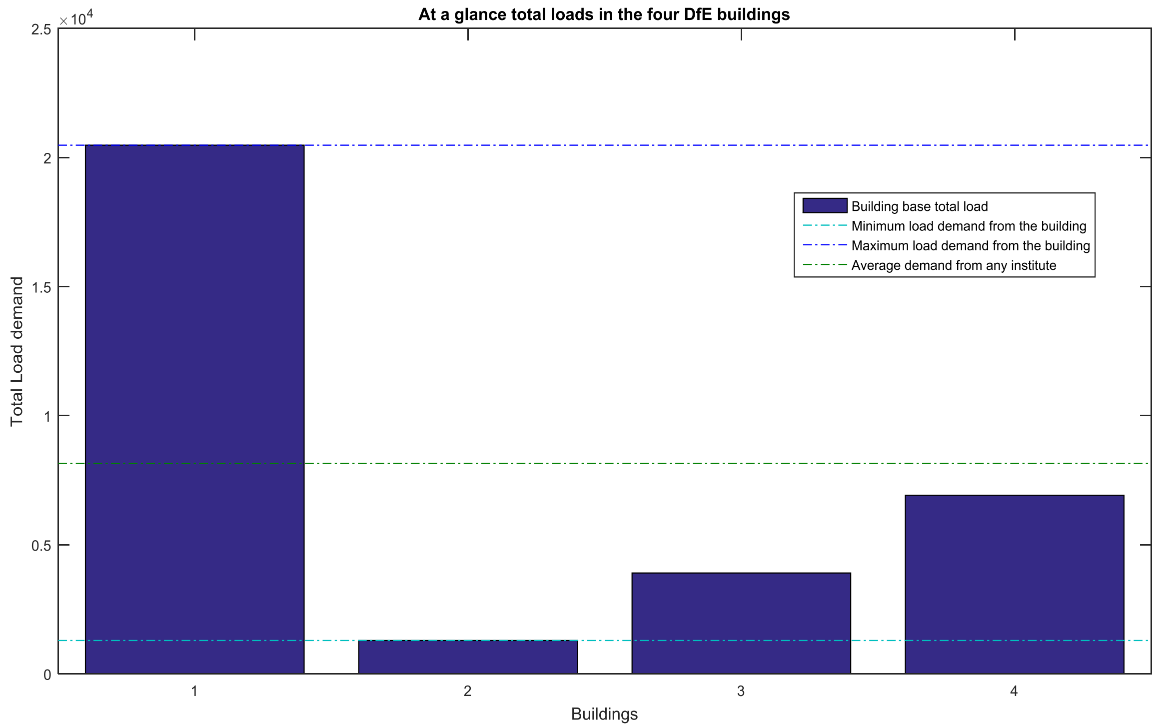

Figure 93: Total loads in the four DfE buildings

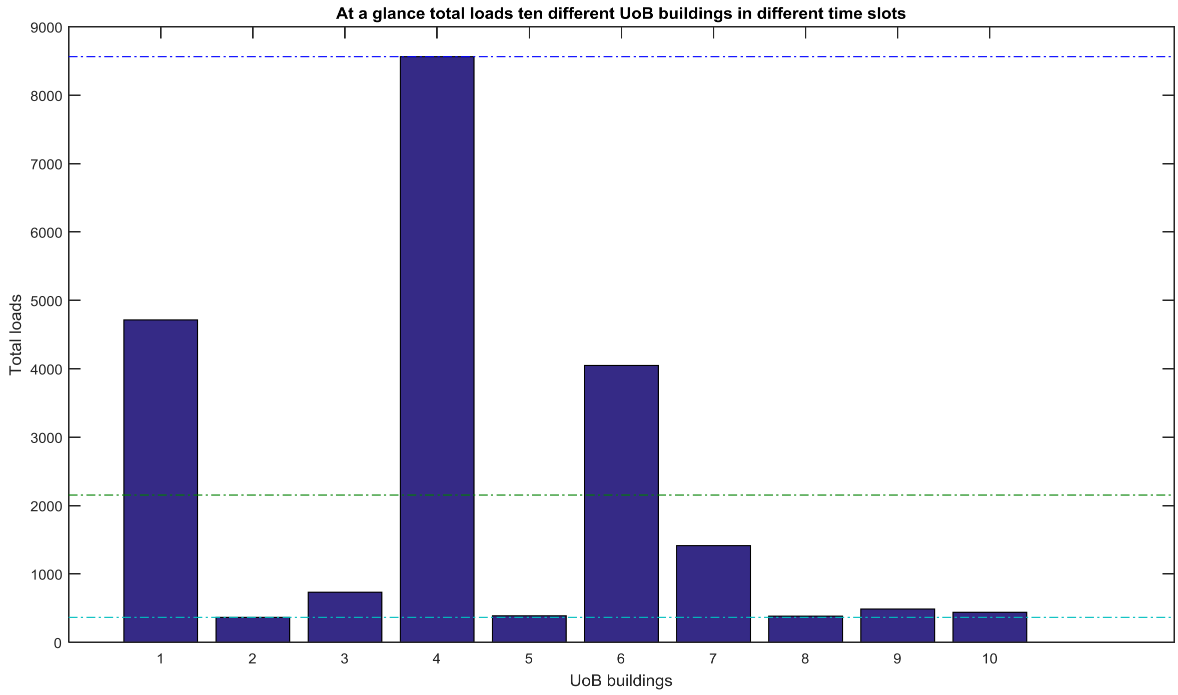

Figure 94: Total load of ten different UoB buildings in different time slots

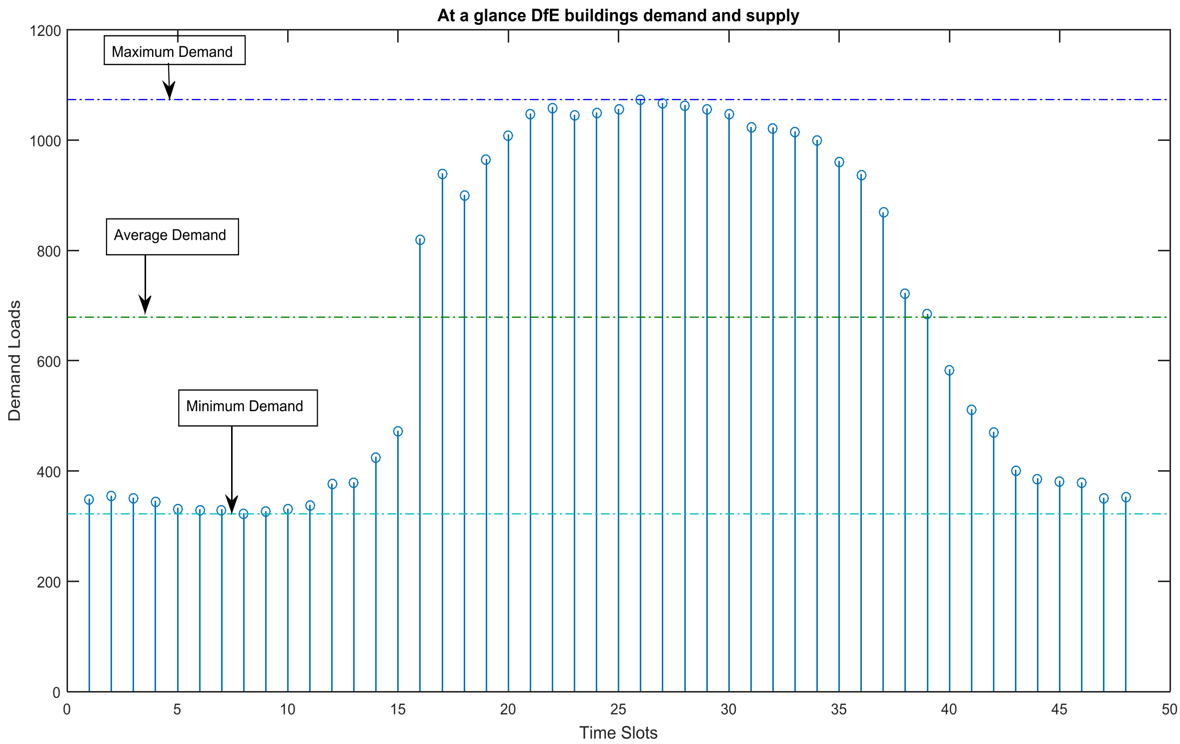

Figure 95: Energy provider's supply regarding users' demand within DfE buildings

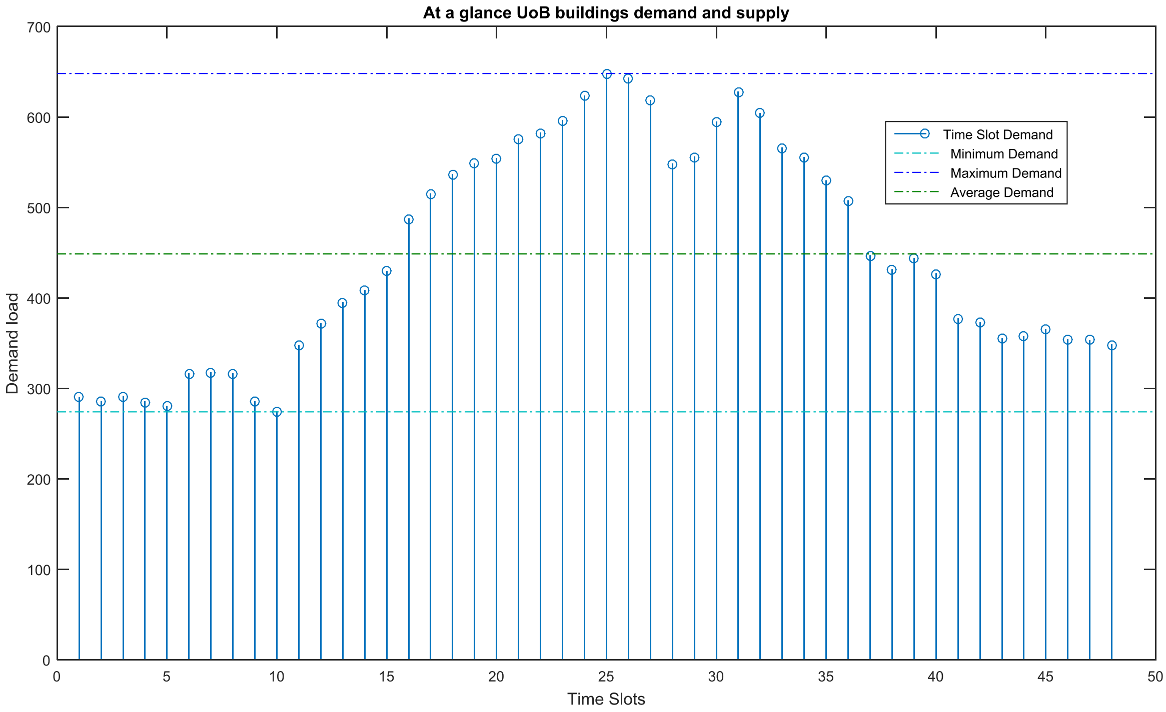

Figure 96: UoB buildings' demand and supply

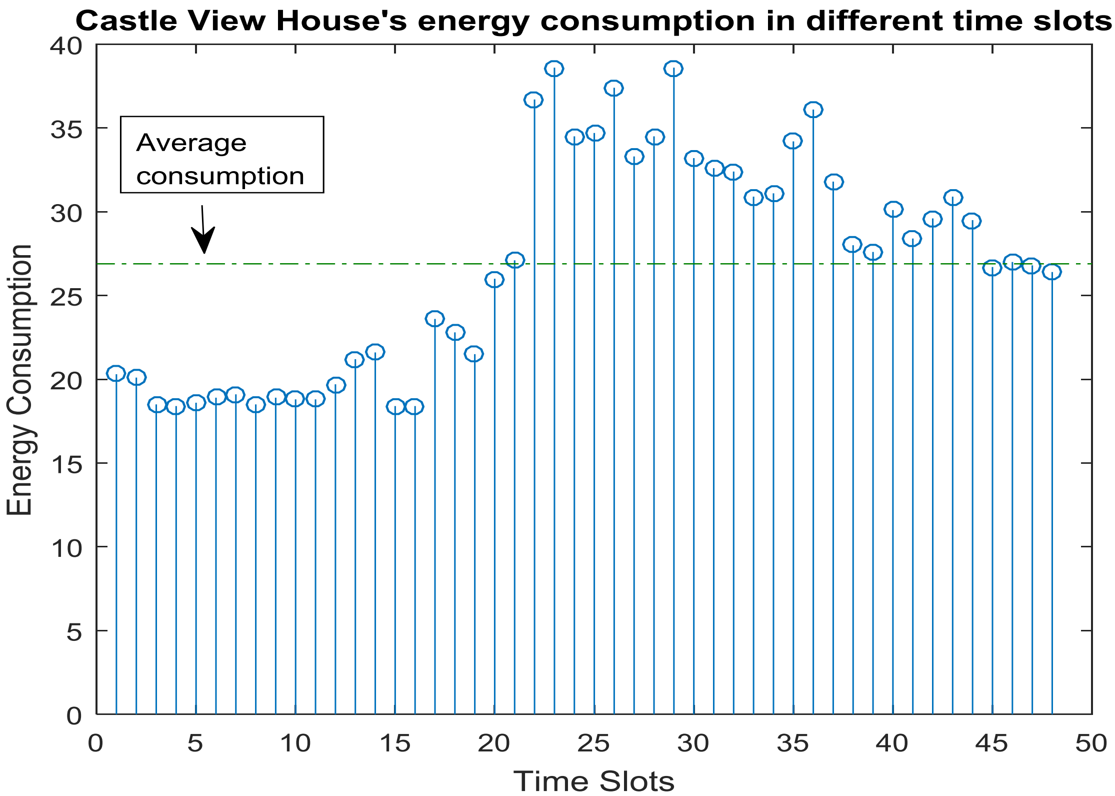

Figure 97: Energy load distribution in Castle View House

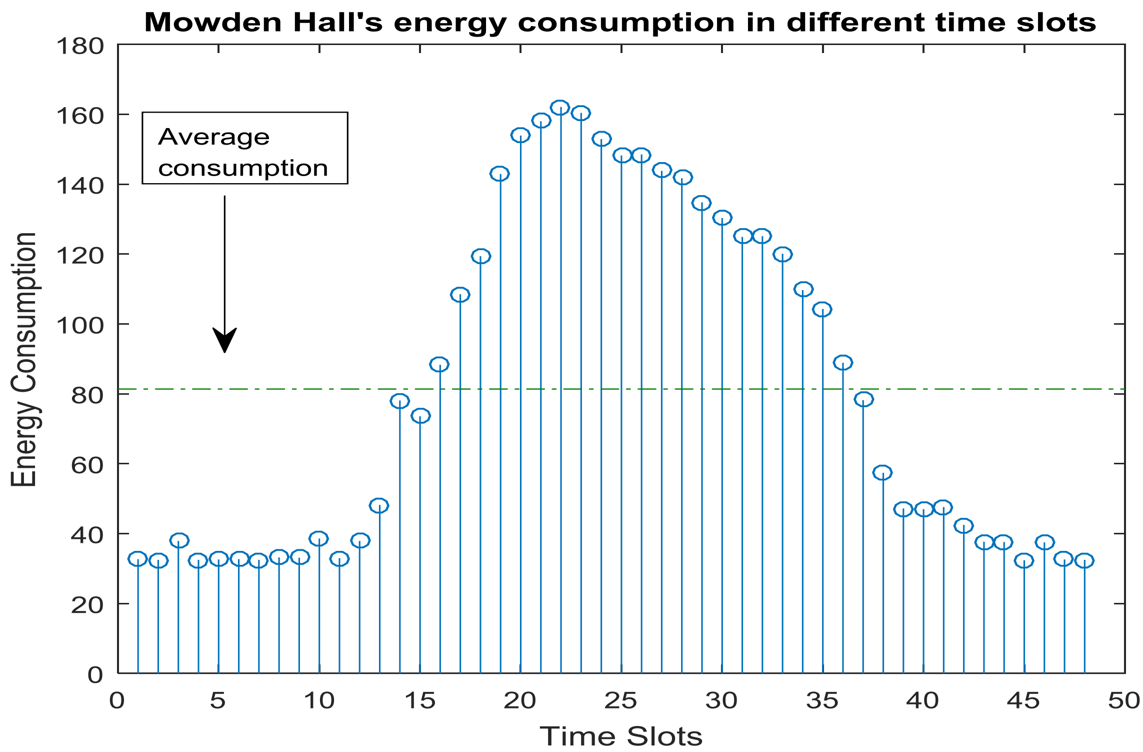

Figure 98: **Energy load distribution in Mowden Hall**

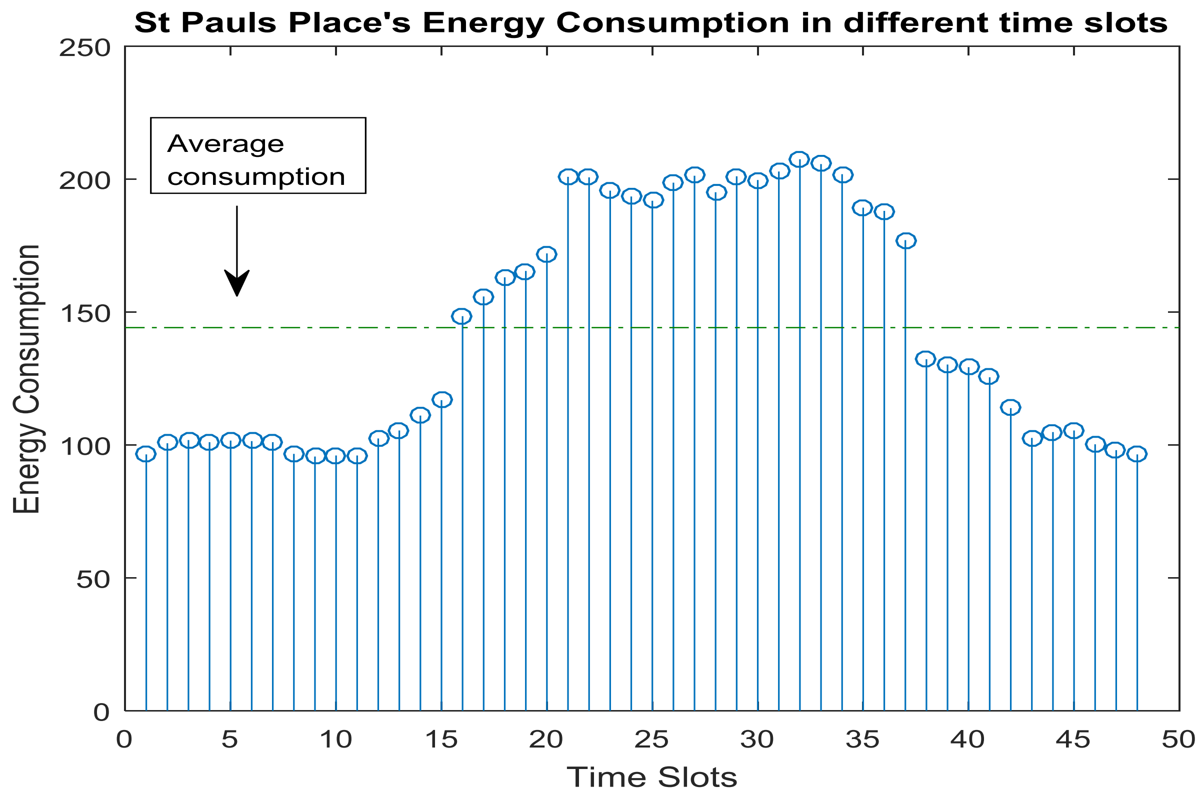

Figure 99: **Energy load distribution in St Pauls Place**

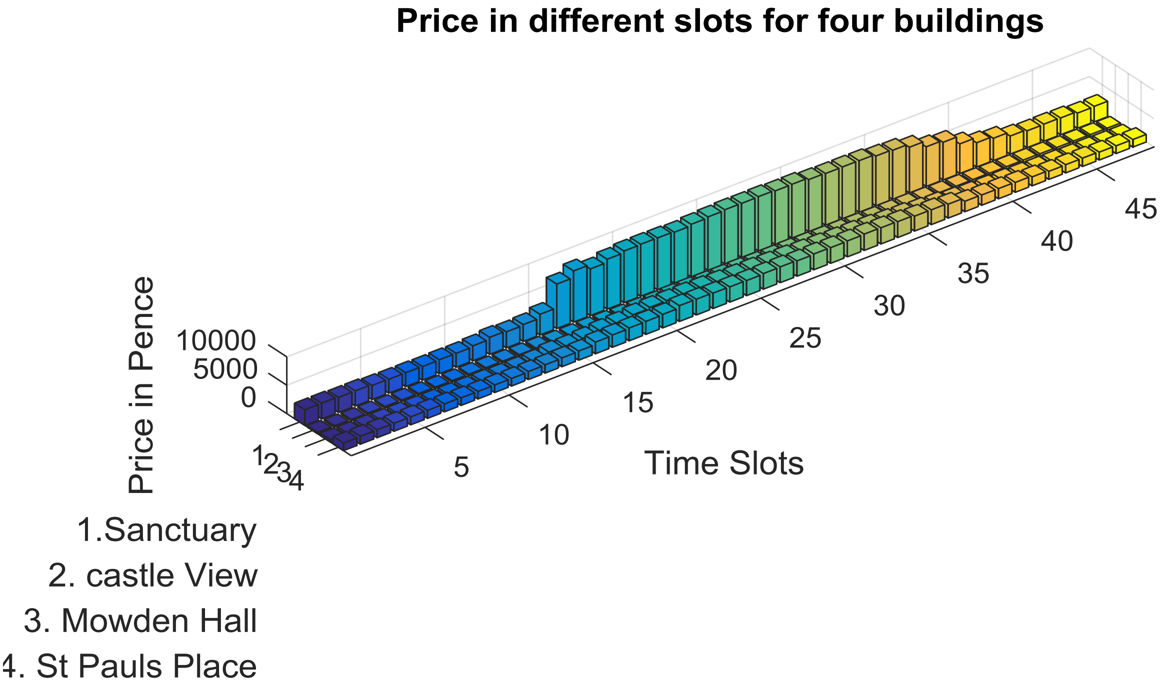

Figure 100: **Price distribution in different time slots 3D in the DfE buildings**

Figure 101: **Flat-rate total price 2D distribution for four buildings of DfE**

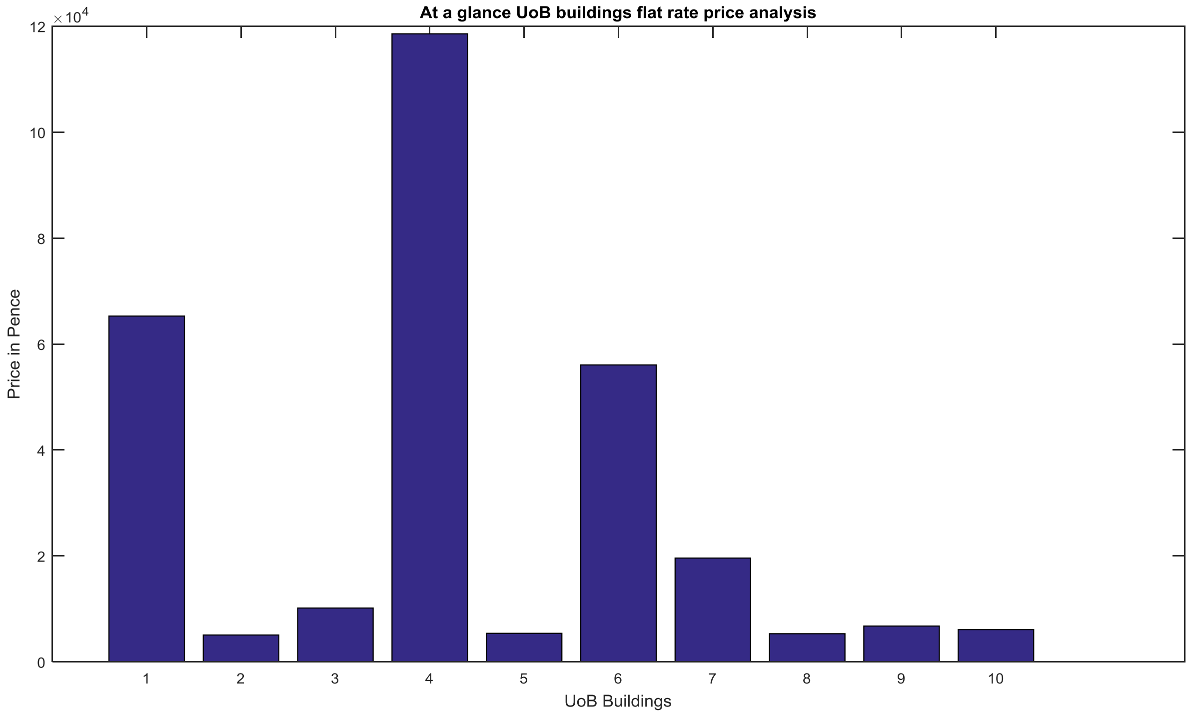

Figure 102: **Flat-rate pricing analysis for UoB**

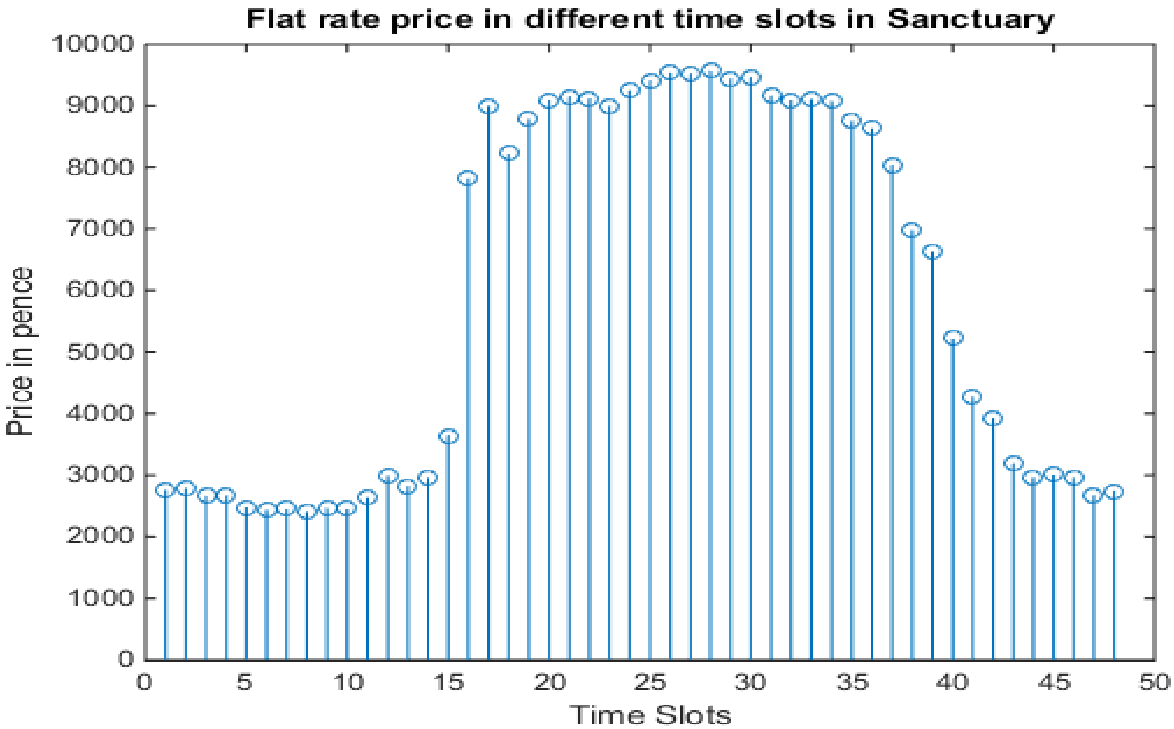

Figure 103: **Flat-rate pricing in the Sanctuary building**

Figure 104: Flat-rate pricing in Castle View House

Figure 105: Flat-rate pricing in Mowden Hall

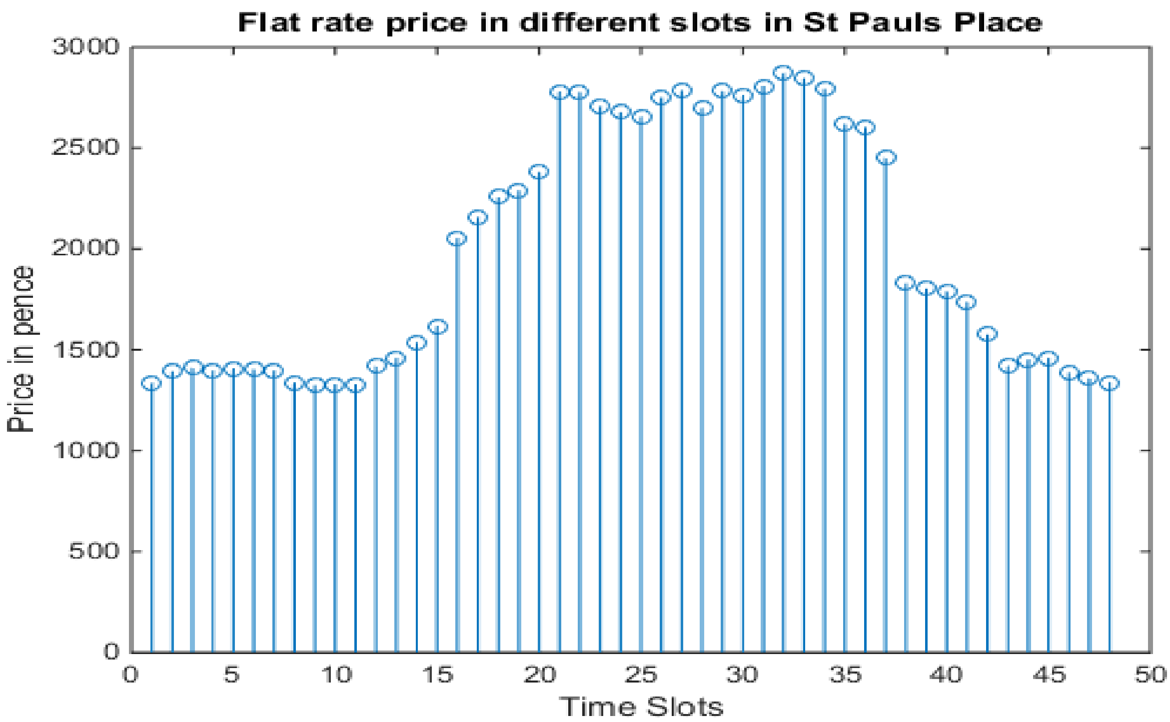

Figure 106: Flat-rate pricing in St Pauls Place

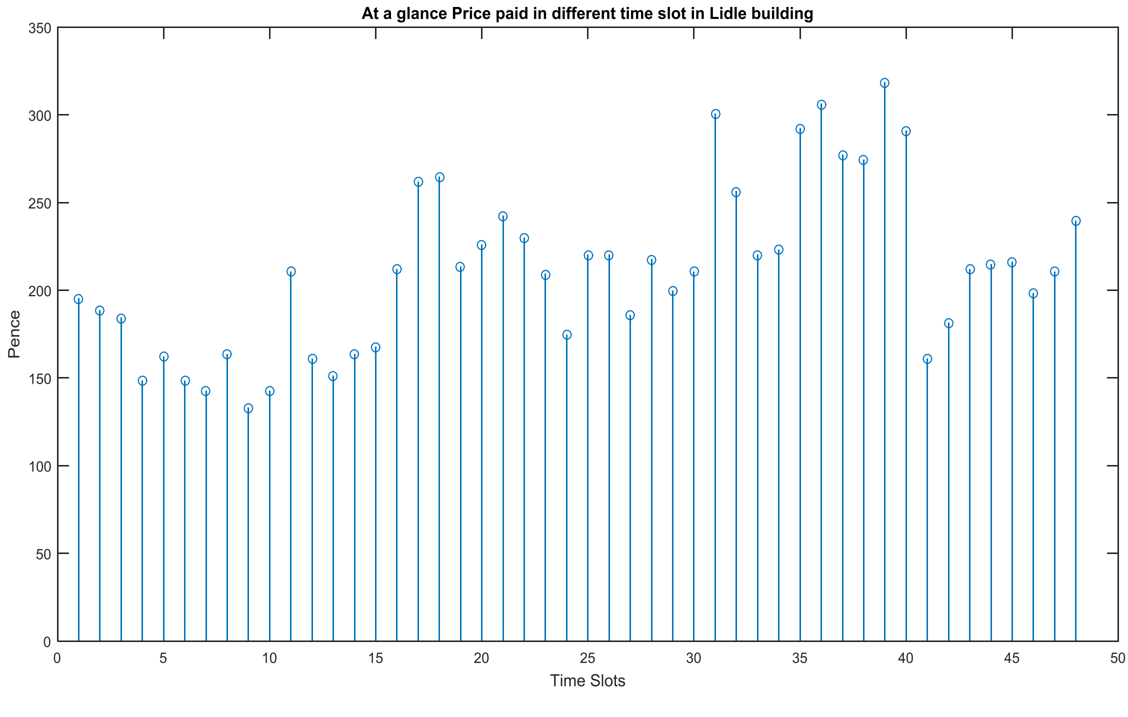

Figure 107: Price paid in different time slots in the Lidle building

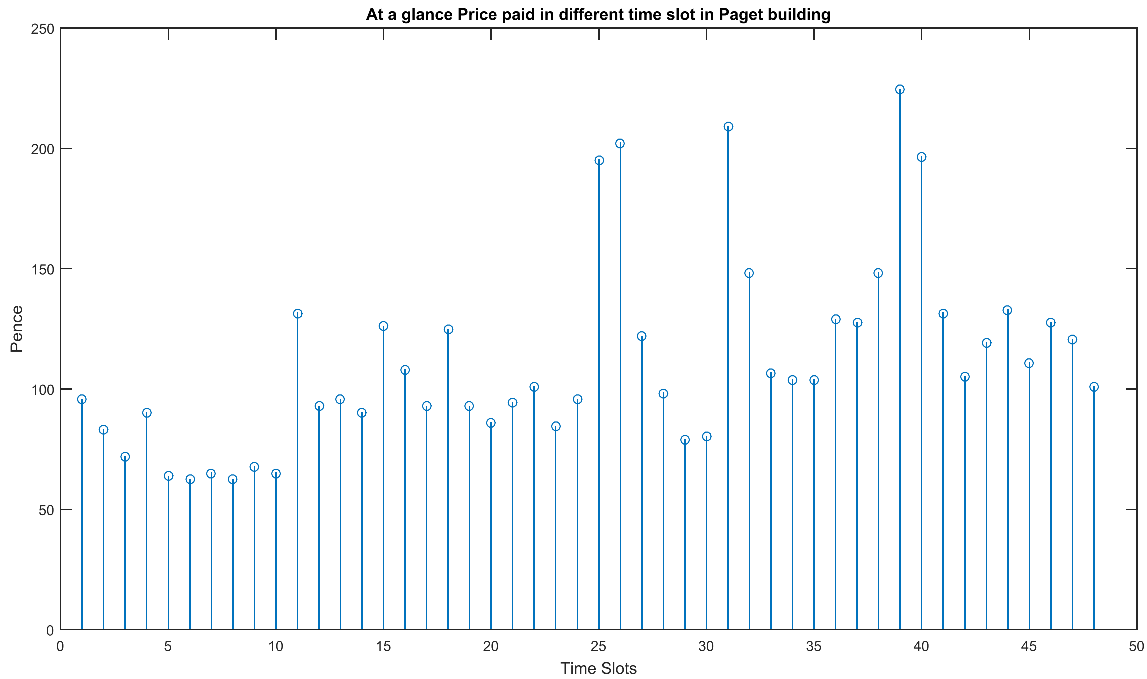

Figure 108: Price paid in different time slots in the Paget building

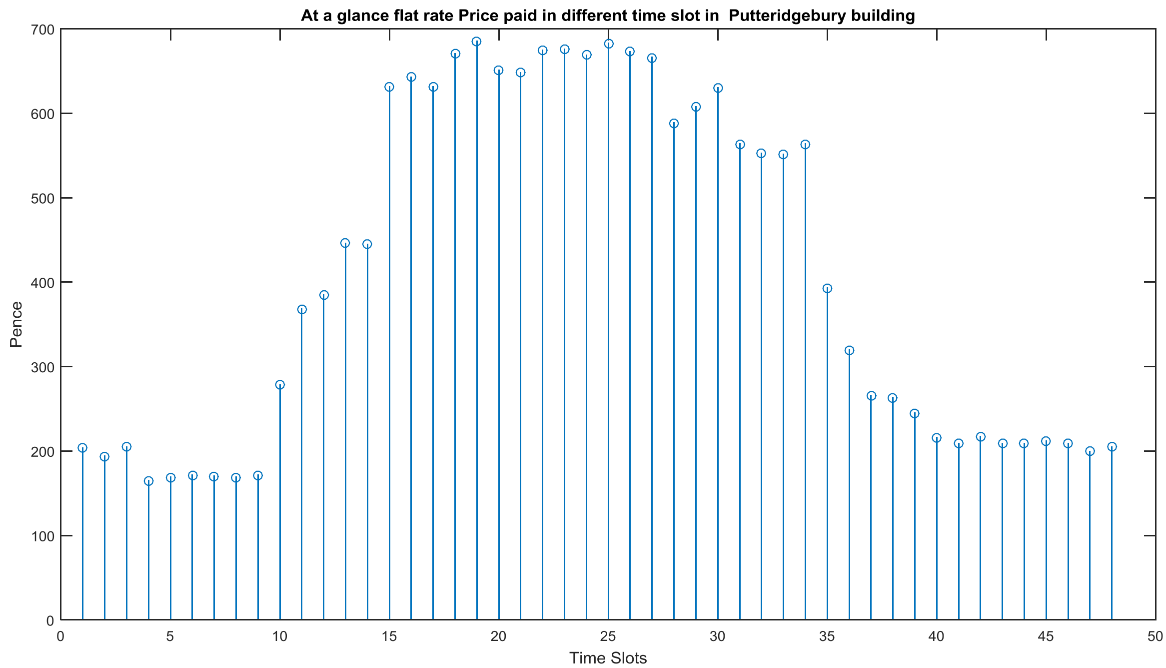

Figure 109: Flat-rate price paid in time slots in the Putteridge Bury building

Figure 110: **Flat-rate price paid in different time slots in the Stephenson building**

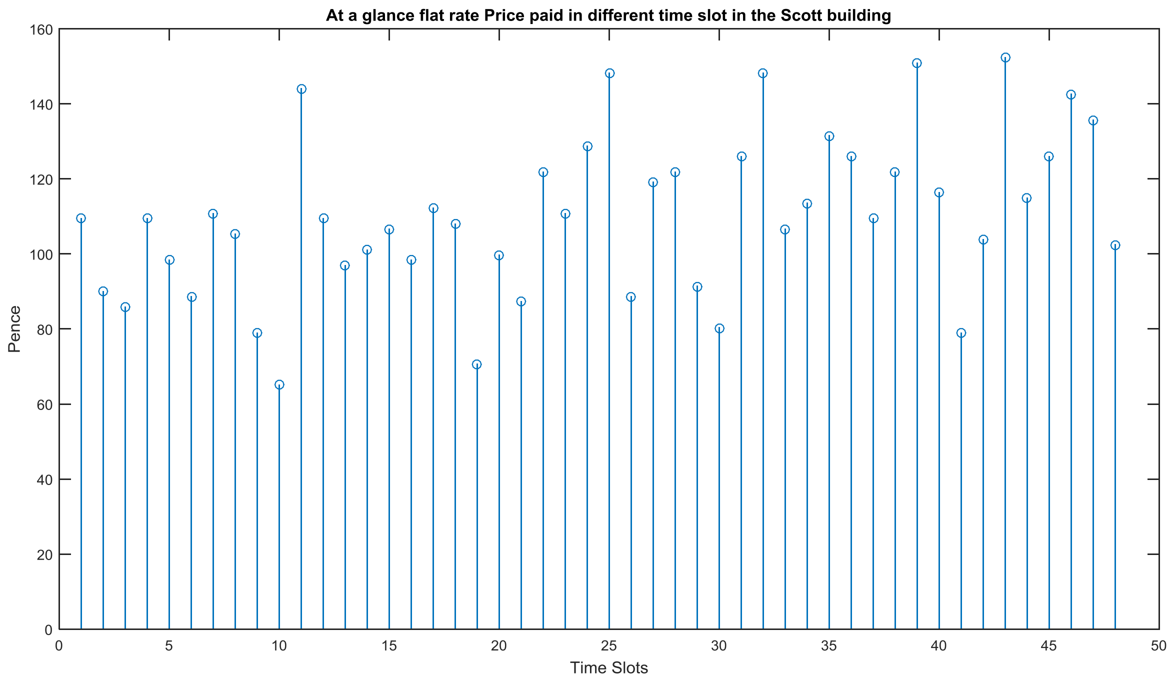

Figure 111: **Flat-rate price paid in different time slots in the Scott building**

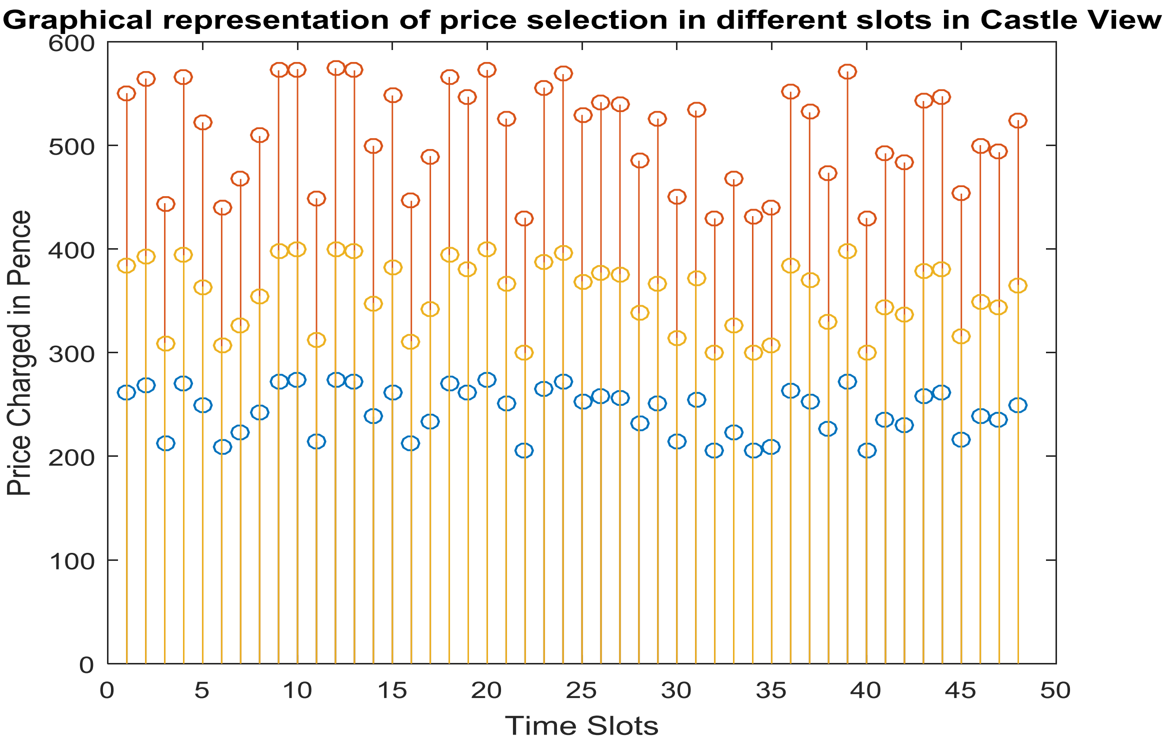

Figure 112: Max, min charges in Castle View Hse for RT price calculation

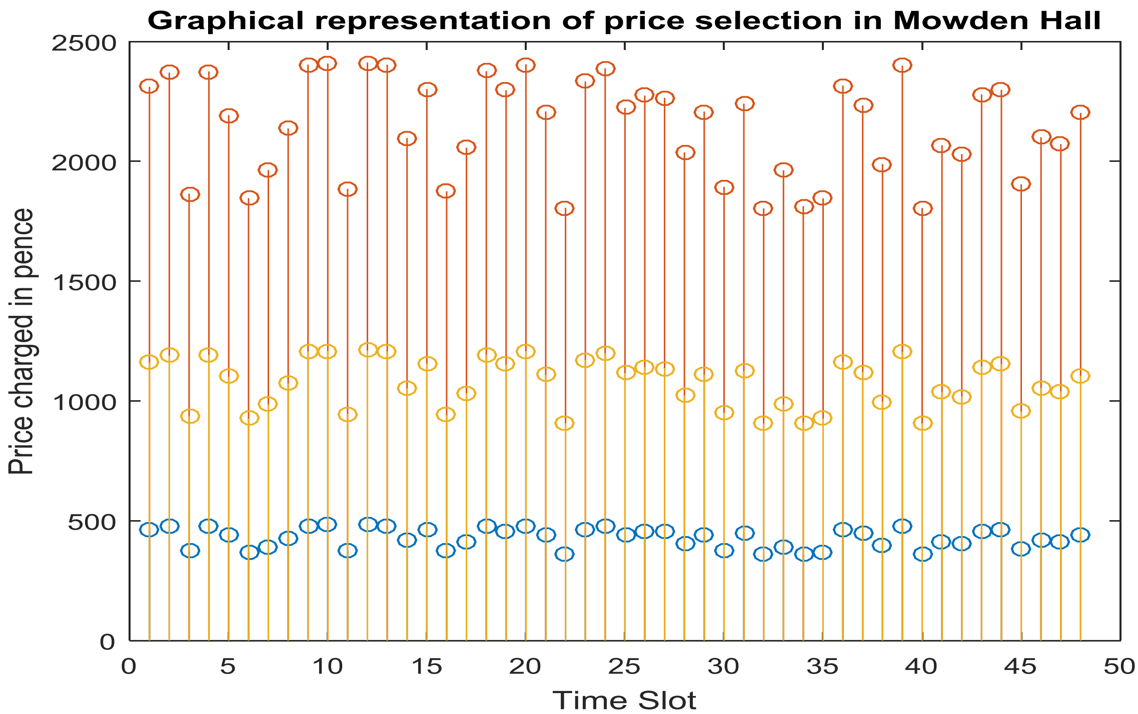

Figure 113: Maximum, minimum charges in Mowden Hall for real-time price calculation

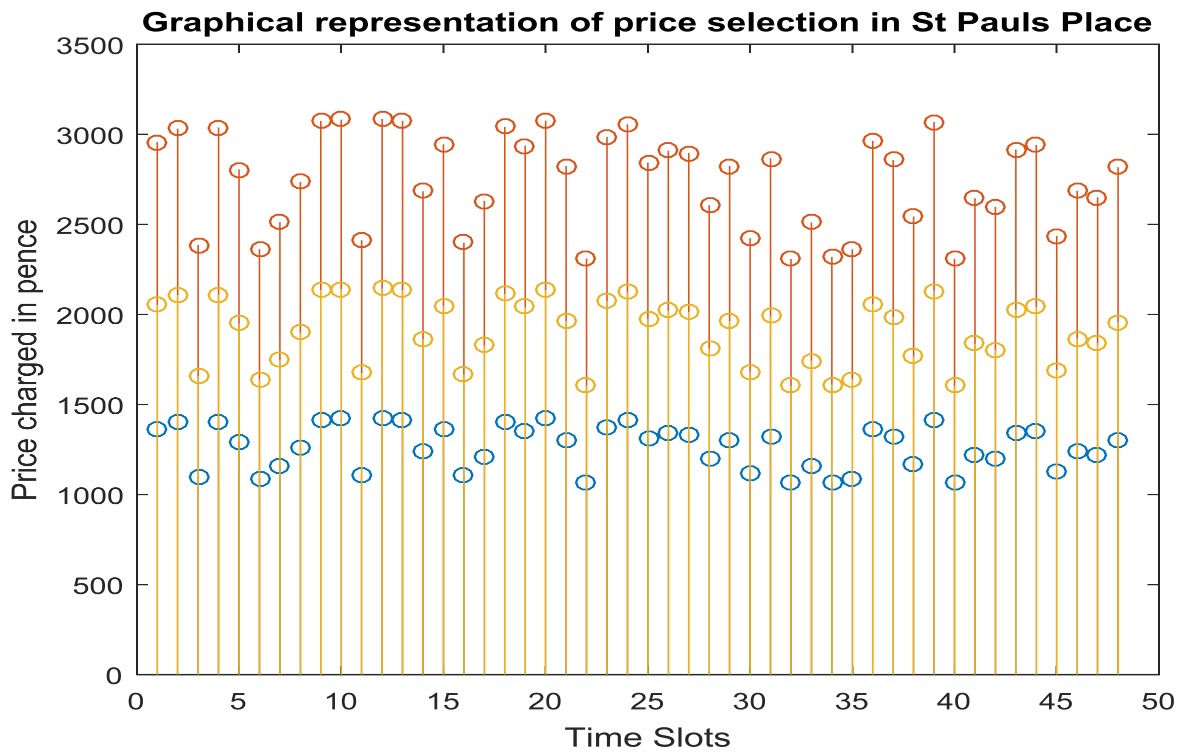

Figure 114: **Maximum, minimum charges in St Pauls Place for real-time price calculation**

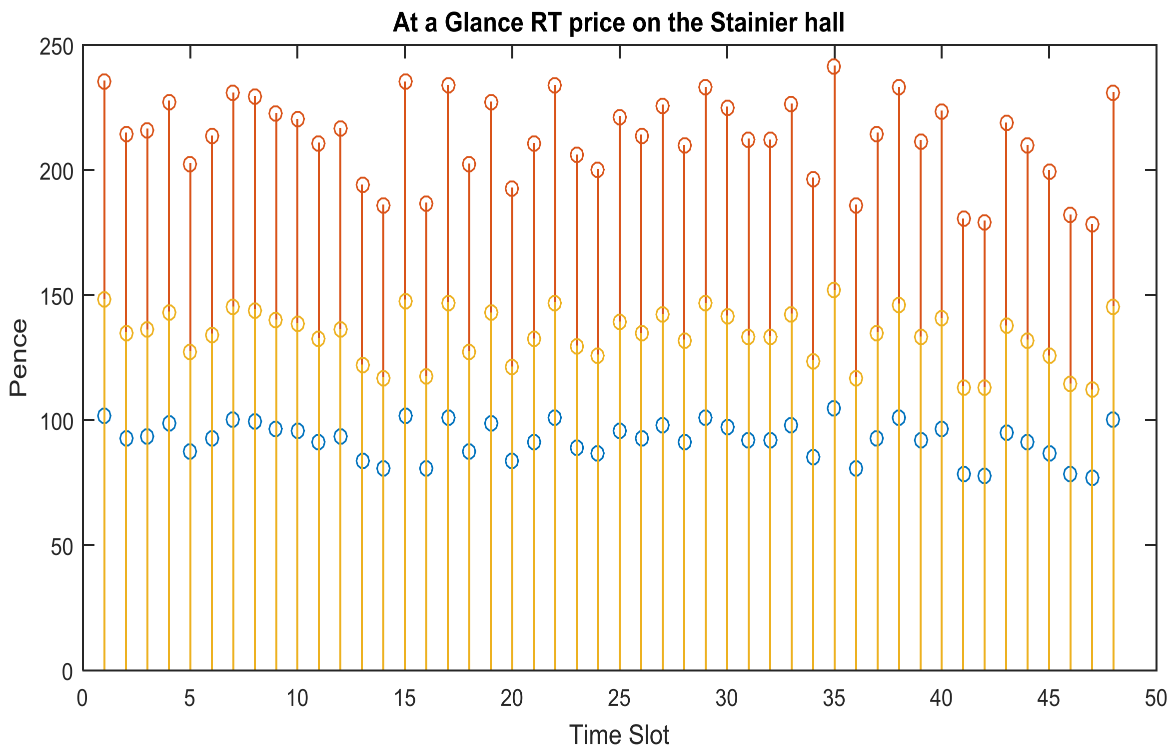

Figure 115: **Maximum, minimum charges in Stainer Hall for real-time price calculation**

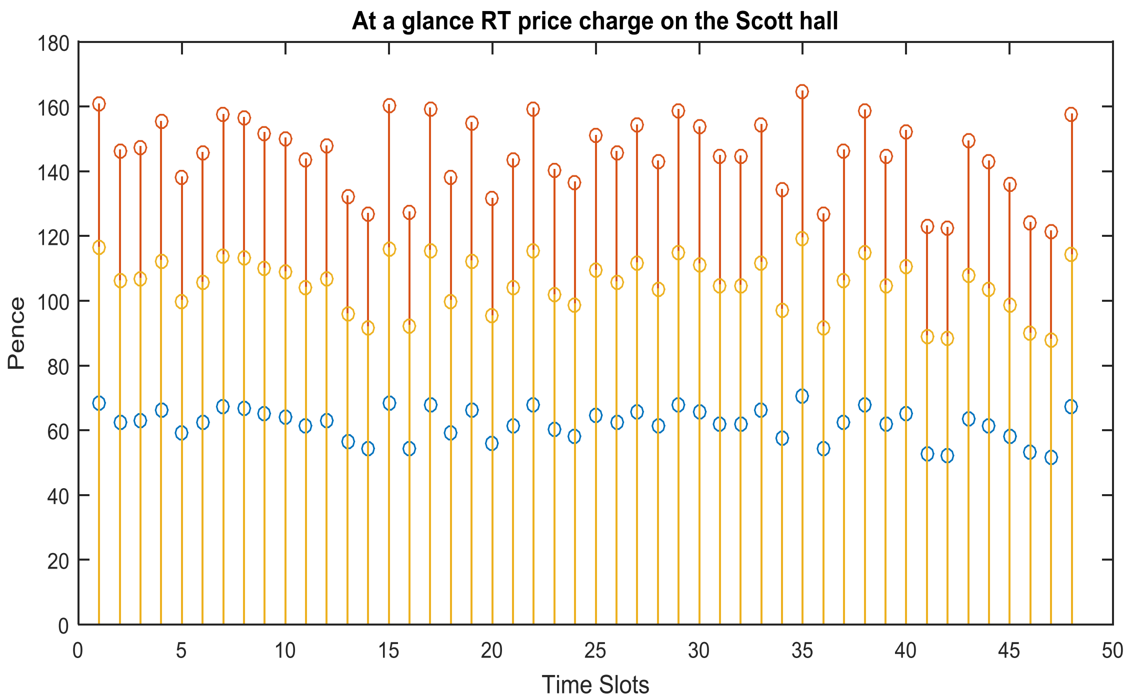

Figure 116: Maximum, minimum charges in Scott Hall for real-time price calculation

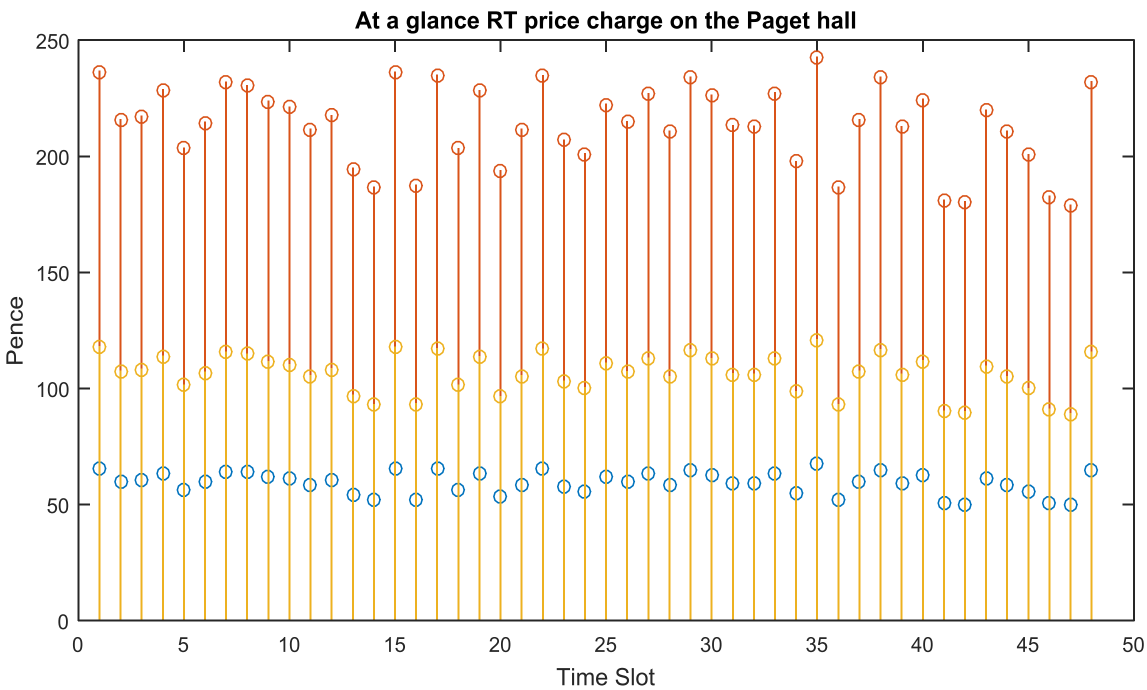

Figure 117: Maximum, minimum charges in Stephen hall for real-time price calculation

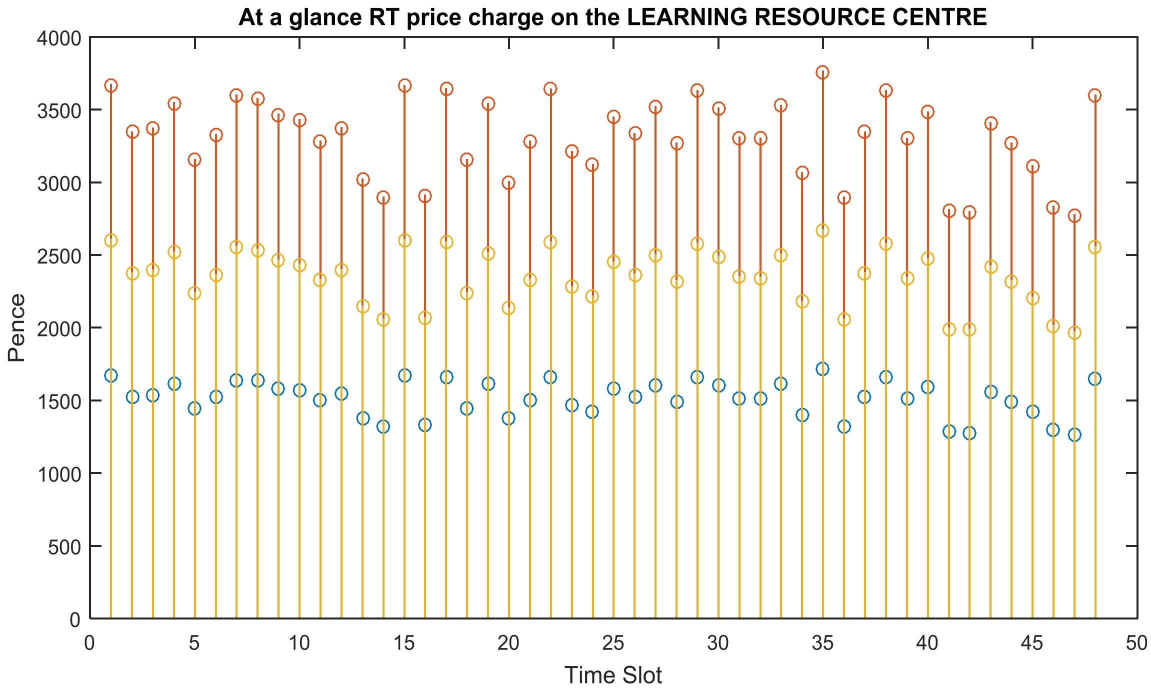

Figure 118: **Maximum, minimum charges in LRC for real-time price calculation**

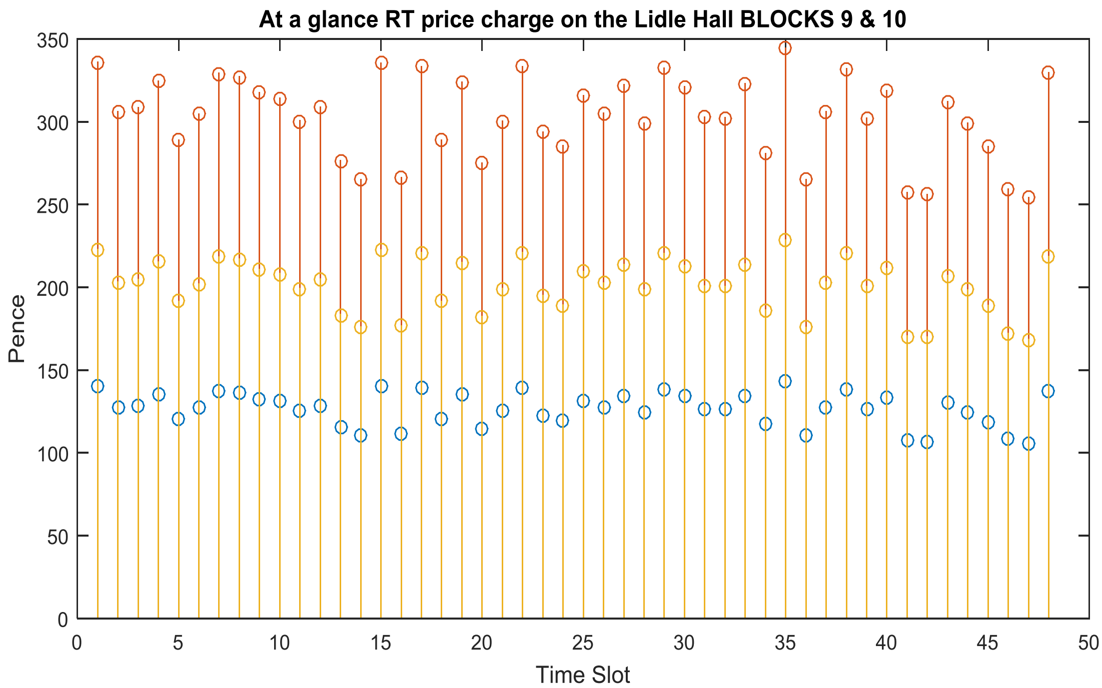

Figure 119: **Maximum, minimum charges in Lidle Hall for real-time price calculation**

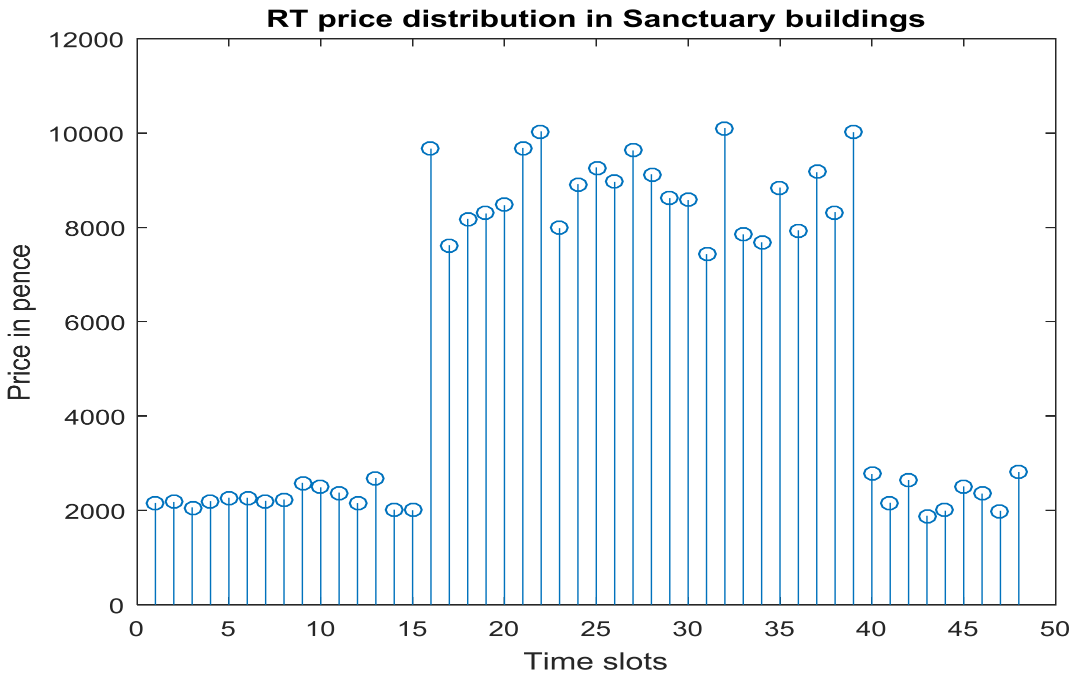

Figure 120: **Real-time pricing in the Sanctuary building**

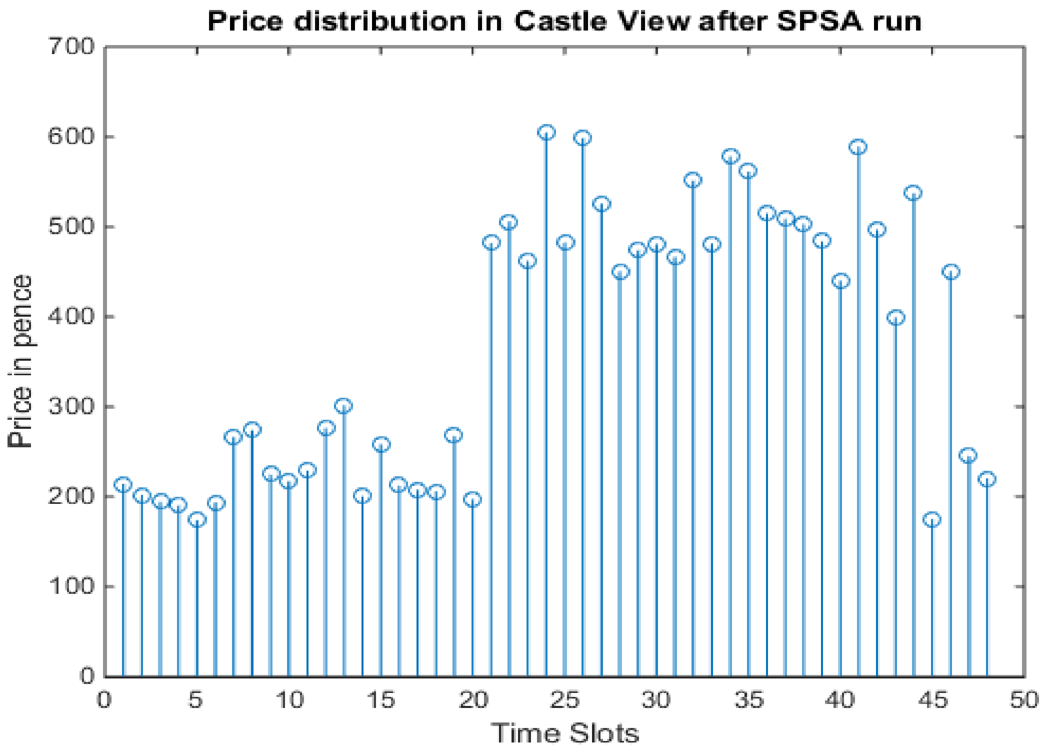

Figure 121: **Real-Time pricing in Castle View House in different slots**

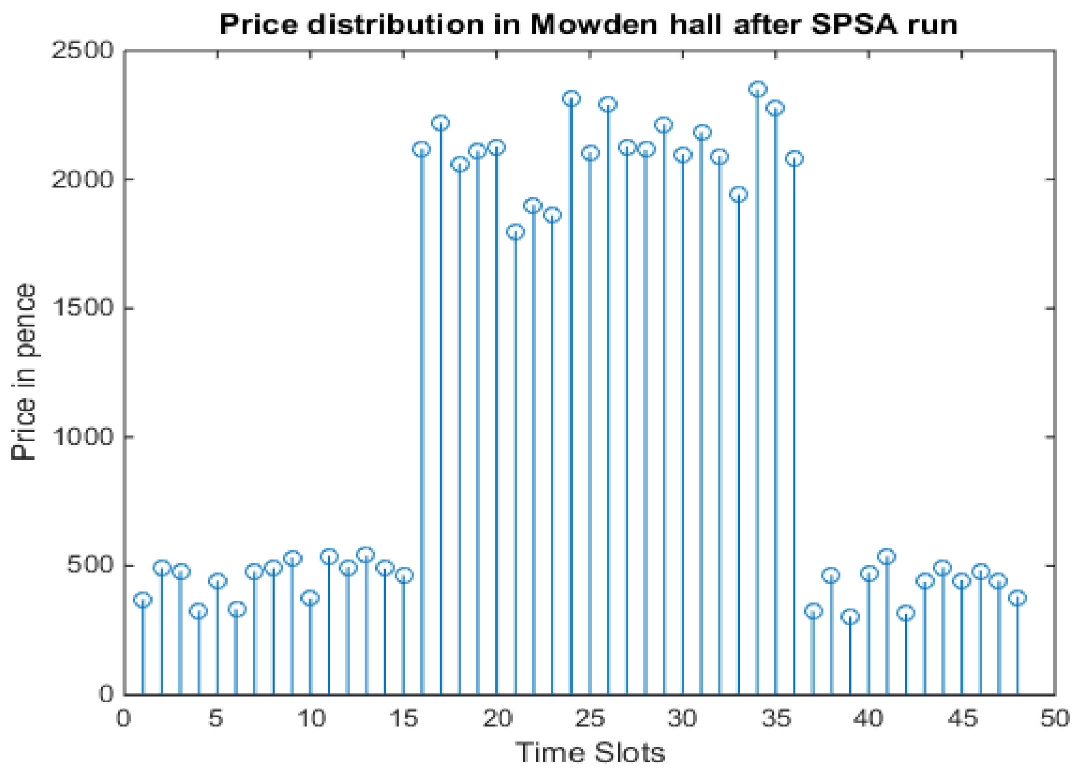

Figure 122: **Real-time pricing in Mowden Hall distribution in different time slots**

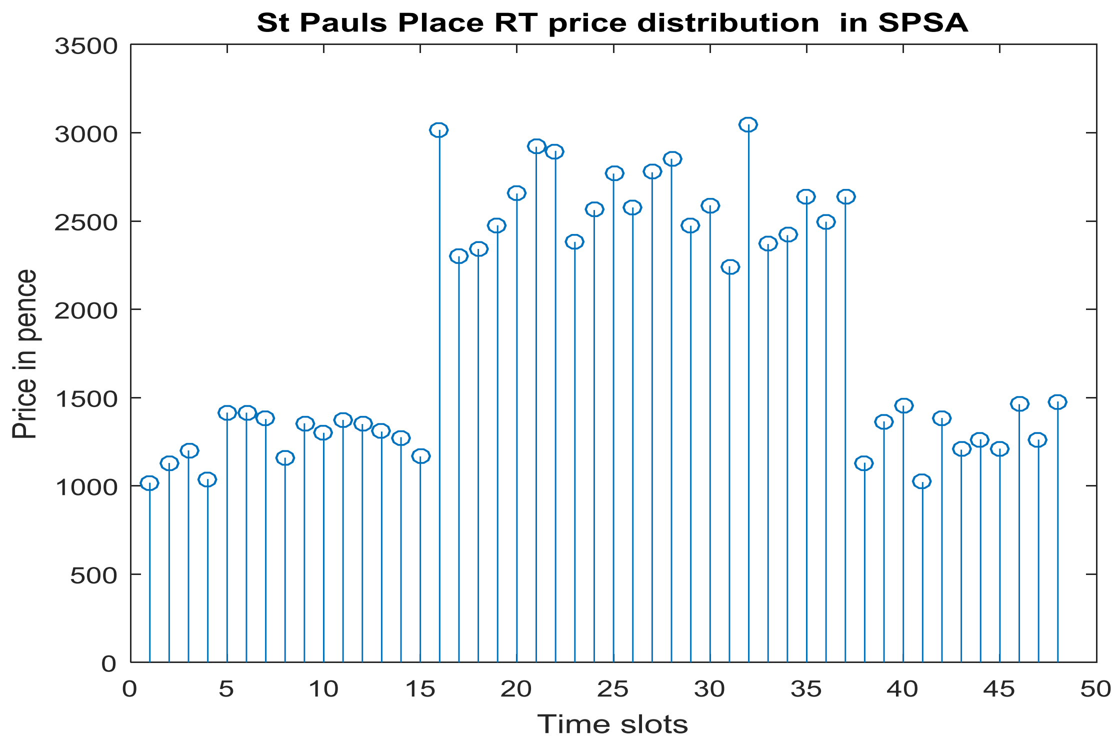

Figure 123: **Real-Time pricing in St Pauls Place in different slots**

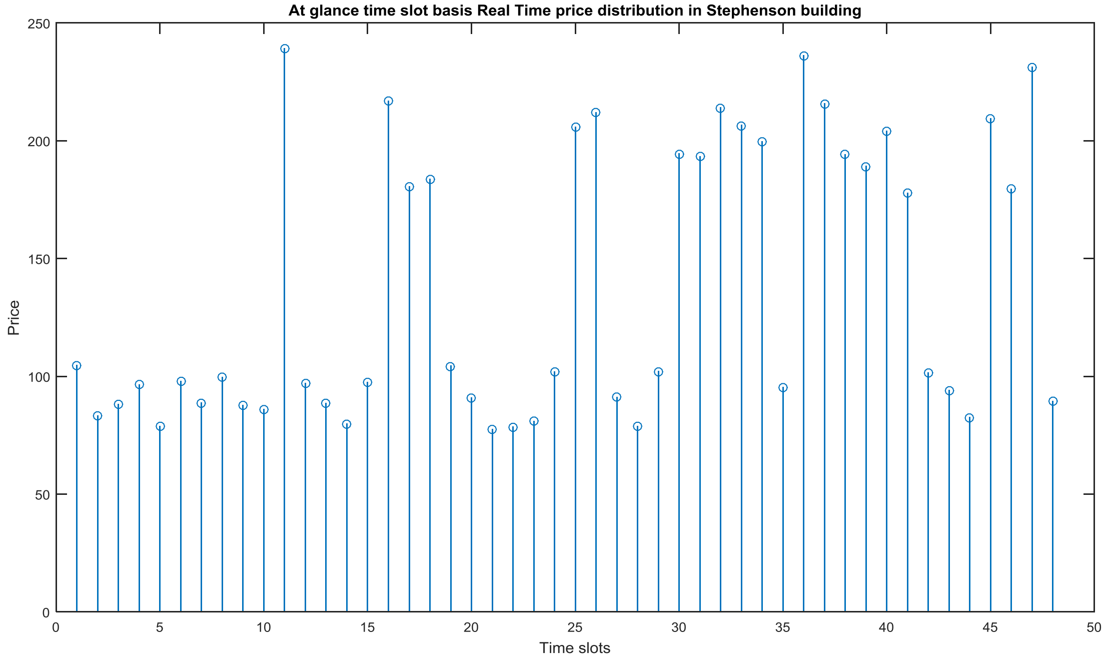

Figure 124: **Time slot basis real-time price distribution in the Stephenson building**

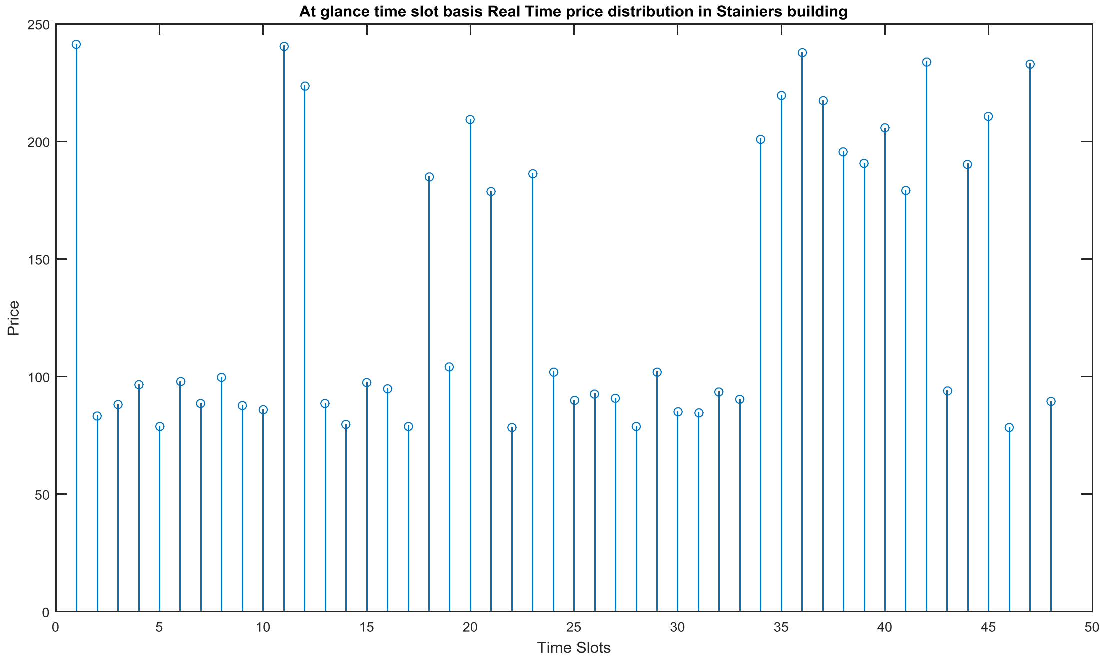

Figure 125: **Time slot basis real-time price distribution in the Stainers building**

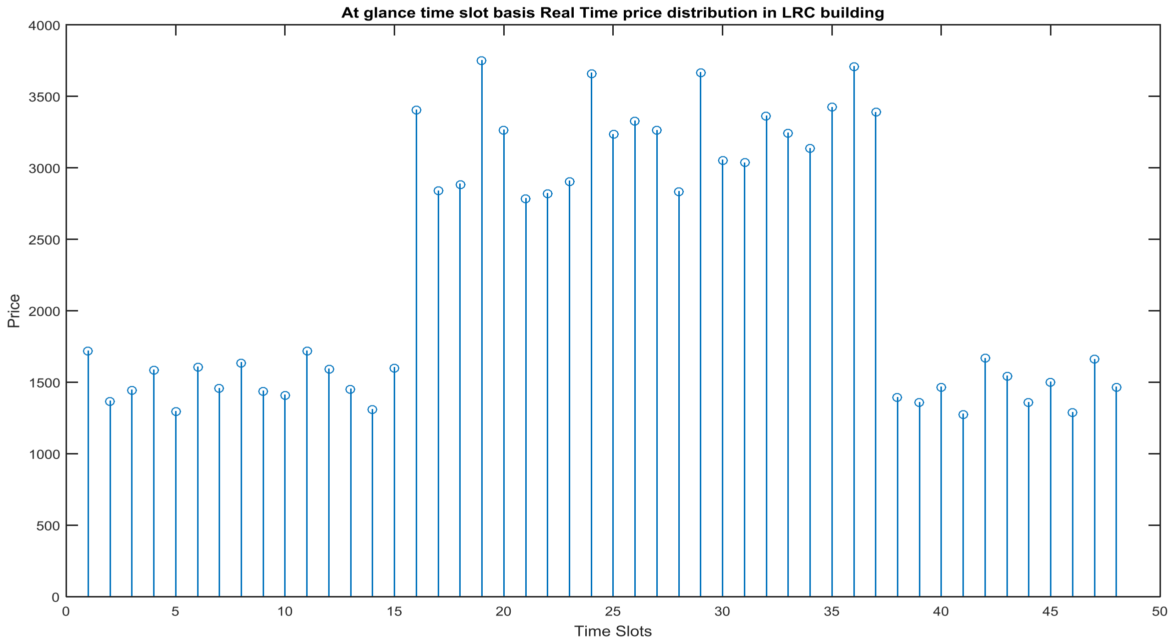

Figure 126: Time slot basis real-time price distribution in the LRC building

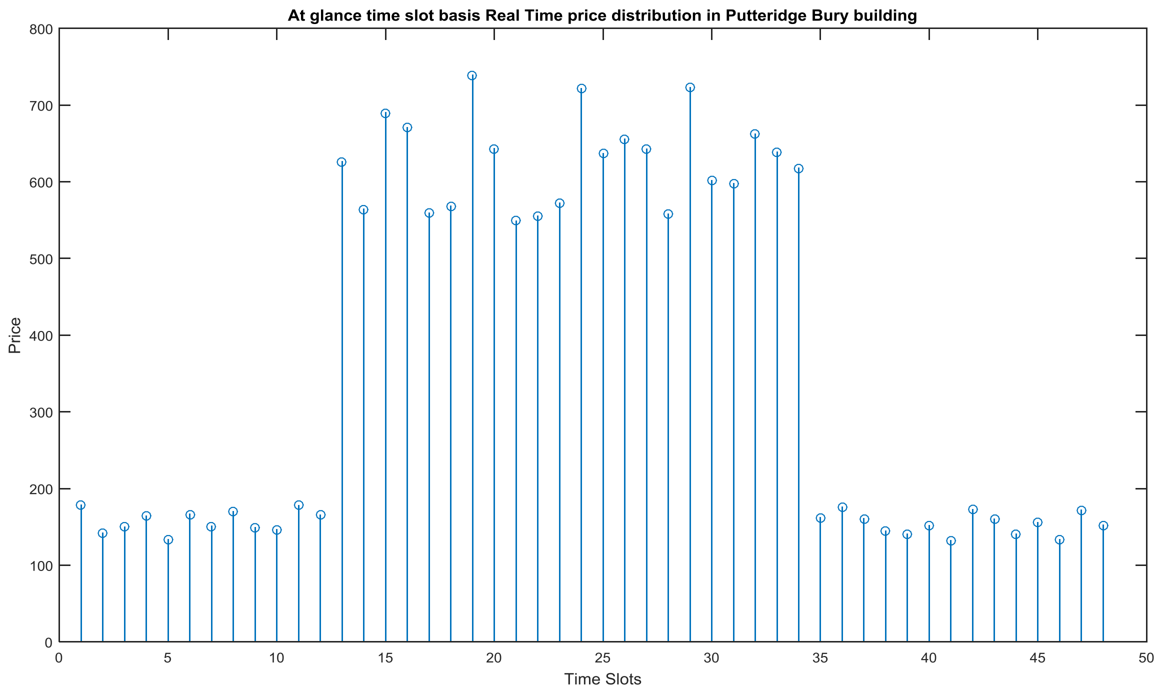

Figure 127: Time slot basis RT price distribution in the Putteridge Bury building

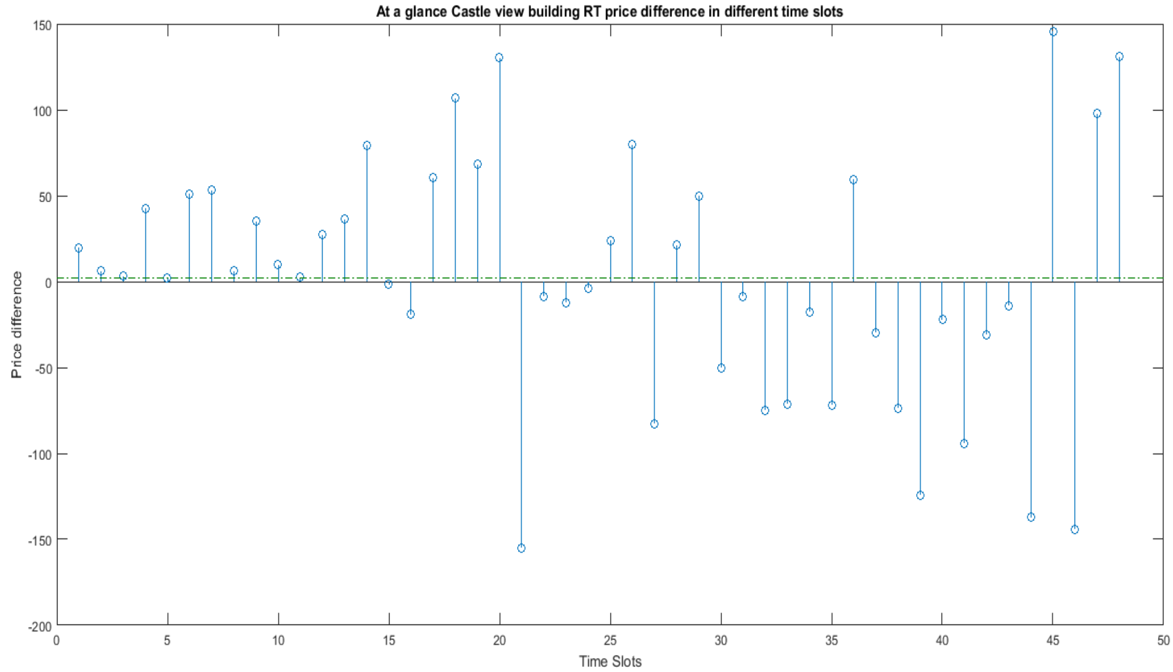

Figure 128: **Price difference in Castle View House from flat rate in different slots**

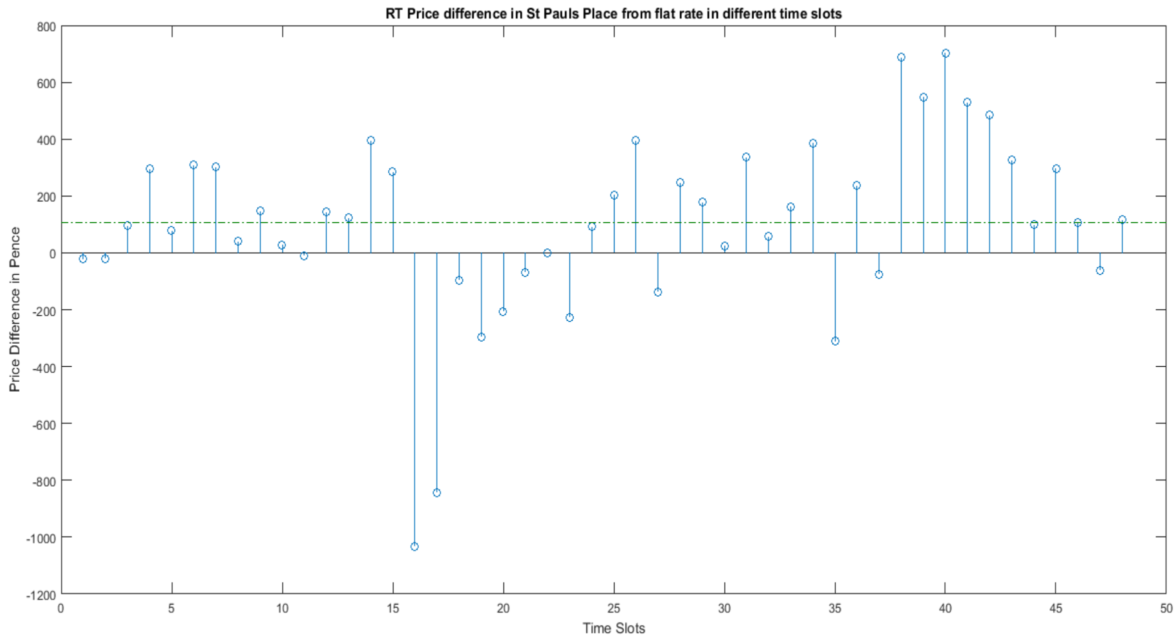

Figure 129: **RT Price difference in St Pauls Place from flat rate in different time slots**

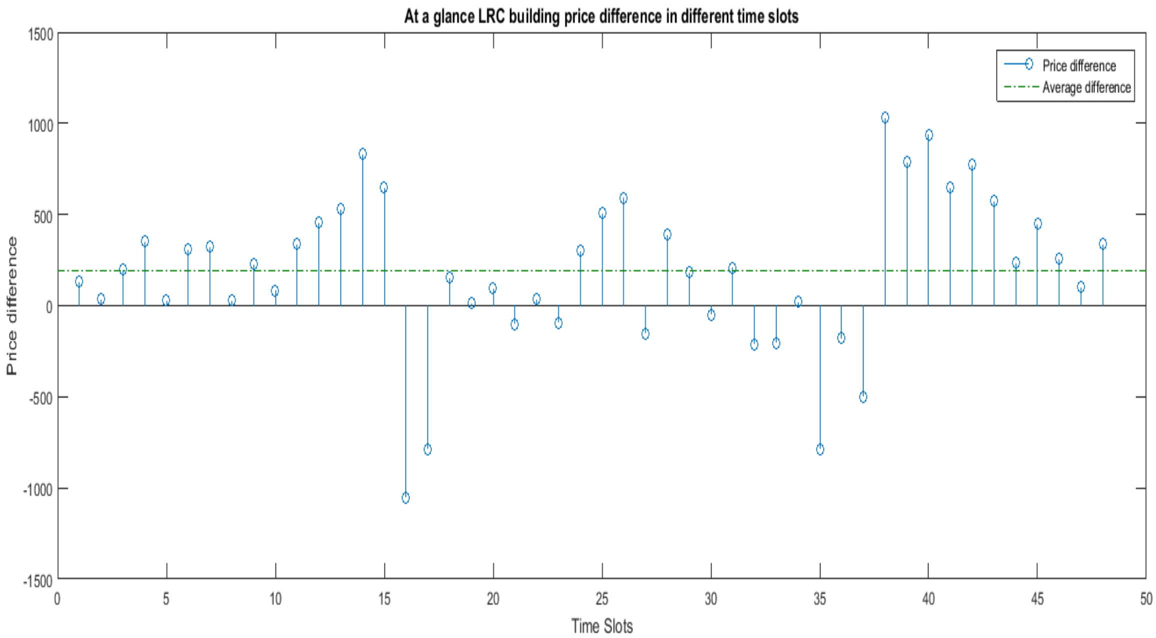

Figure 130: **LRC building price difference in different time slots**

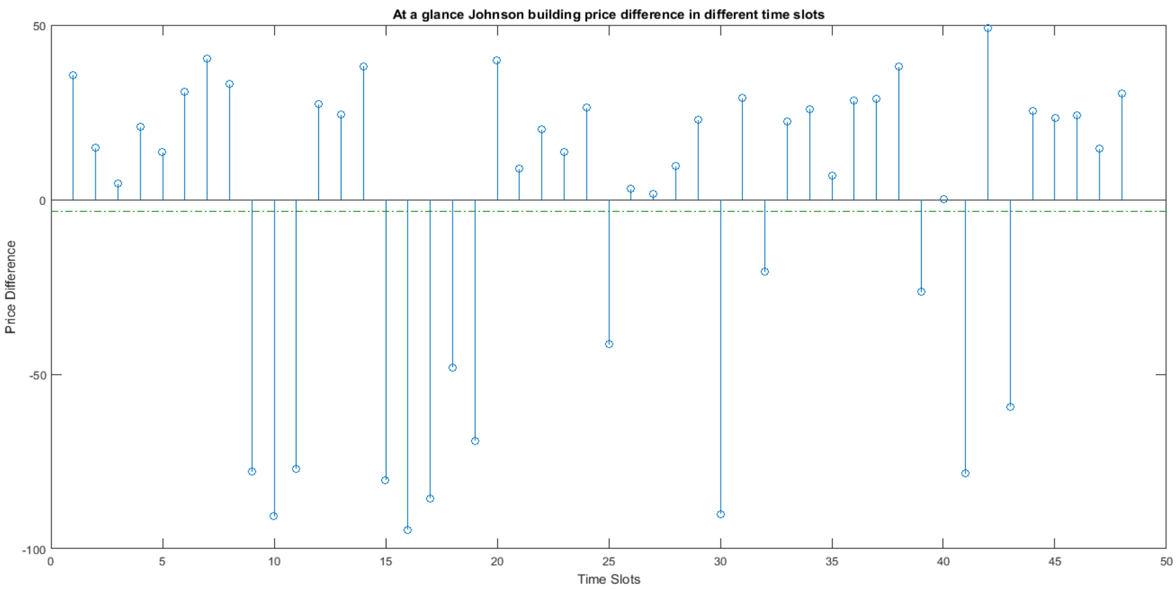

Figure 131: **Johnson building price difference in different time slots**

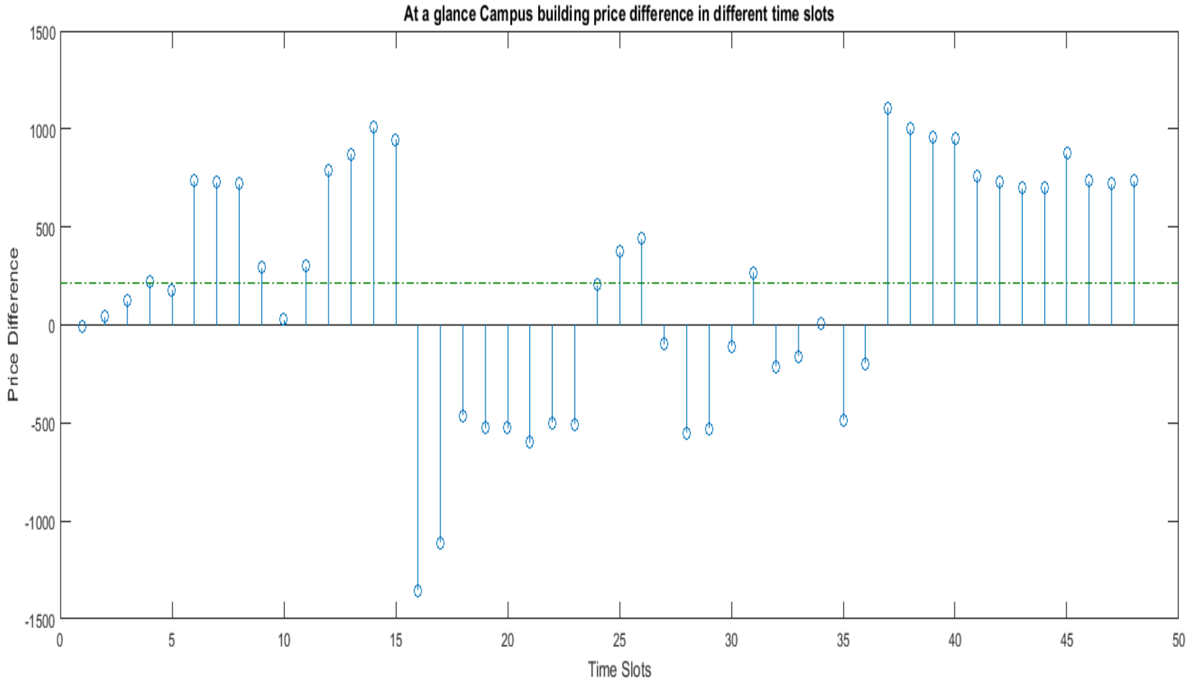

Figure 132: **Campus building price difference in different time slots**

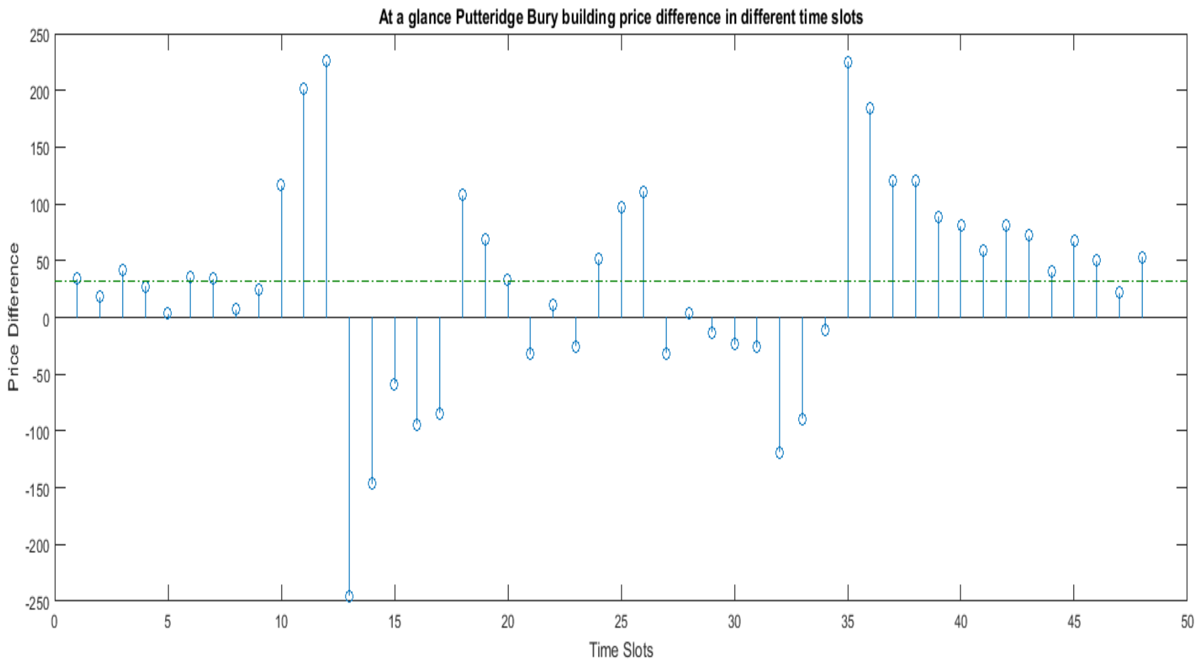

Figure 133: **Putteridge Bury building price difference in different time slots**

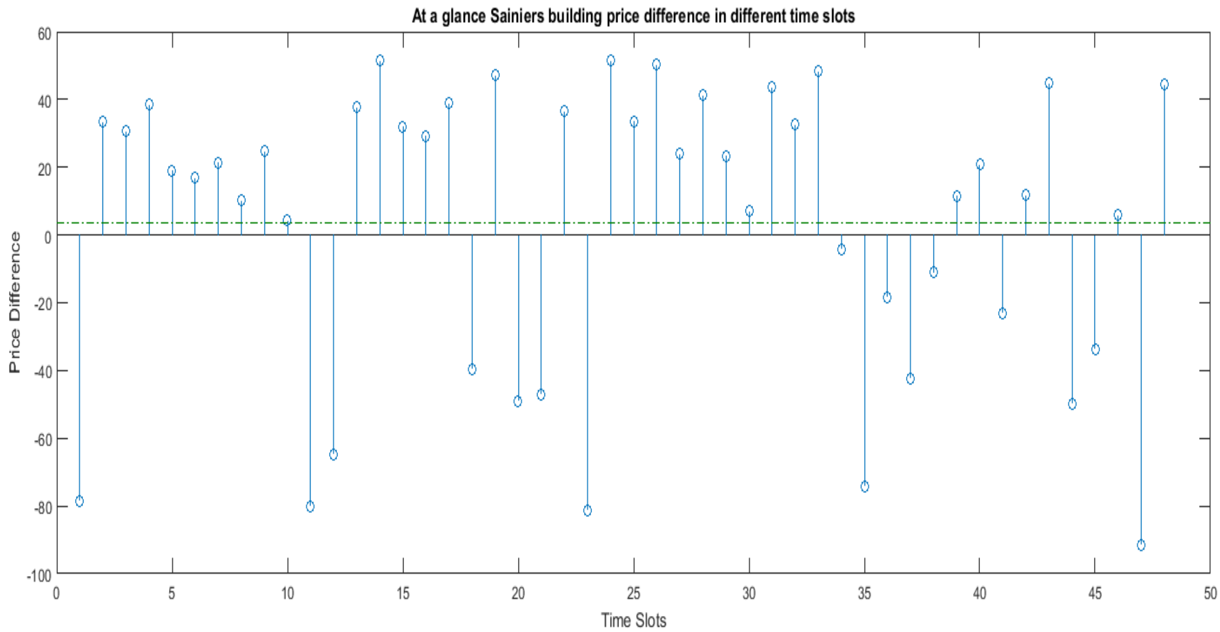

Figure 134: **Sainiers building price difference in different time slots**

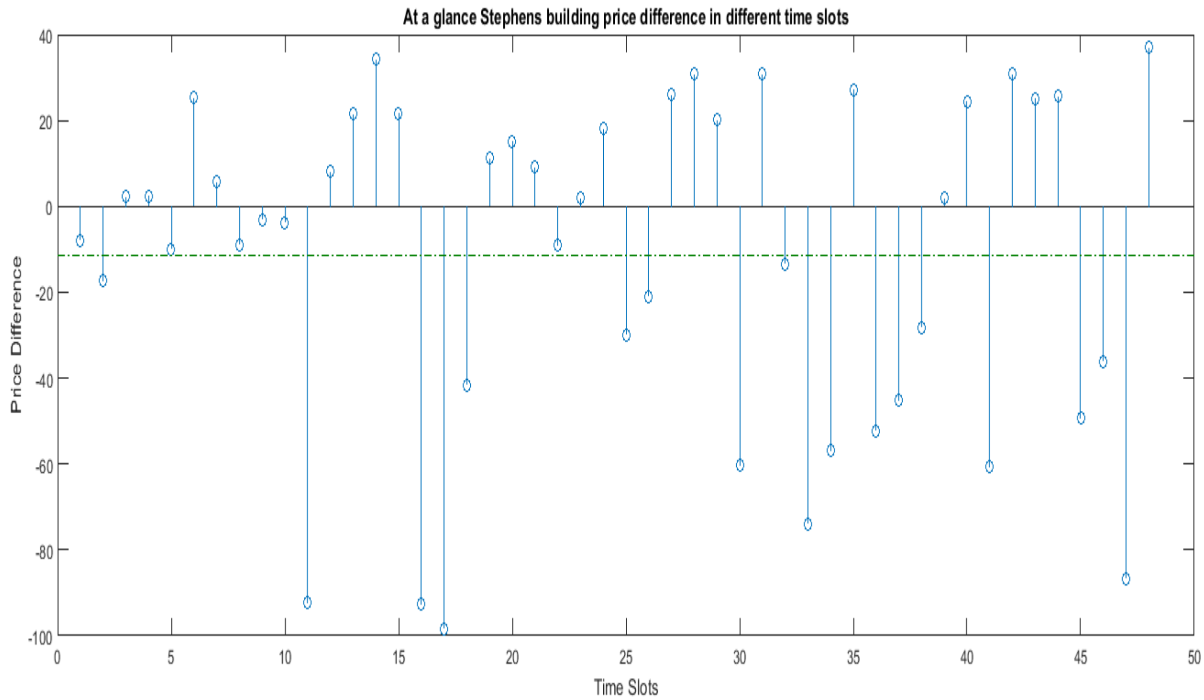

Figure 135: **Stephenson building price difference in different time slots**

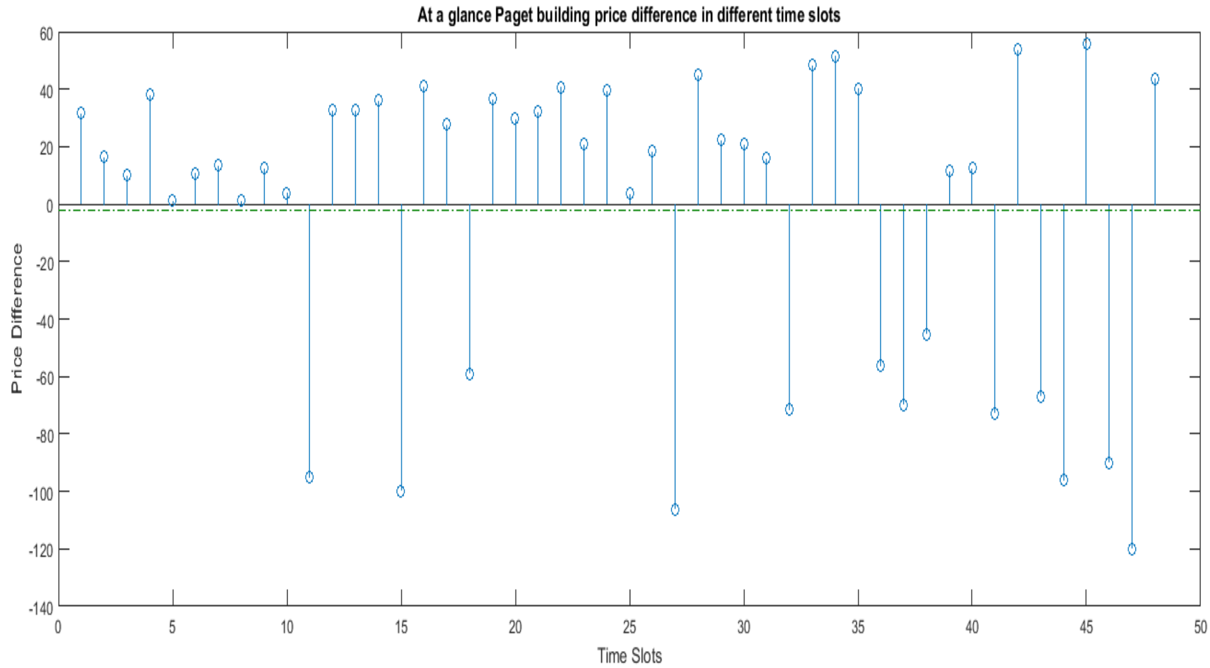

Figure 136: **Paget building price difference in different time slots**

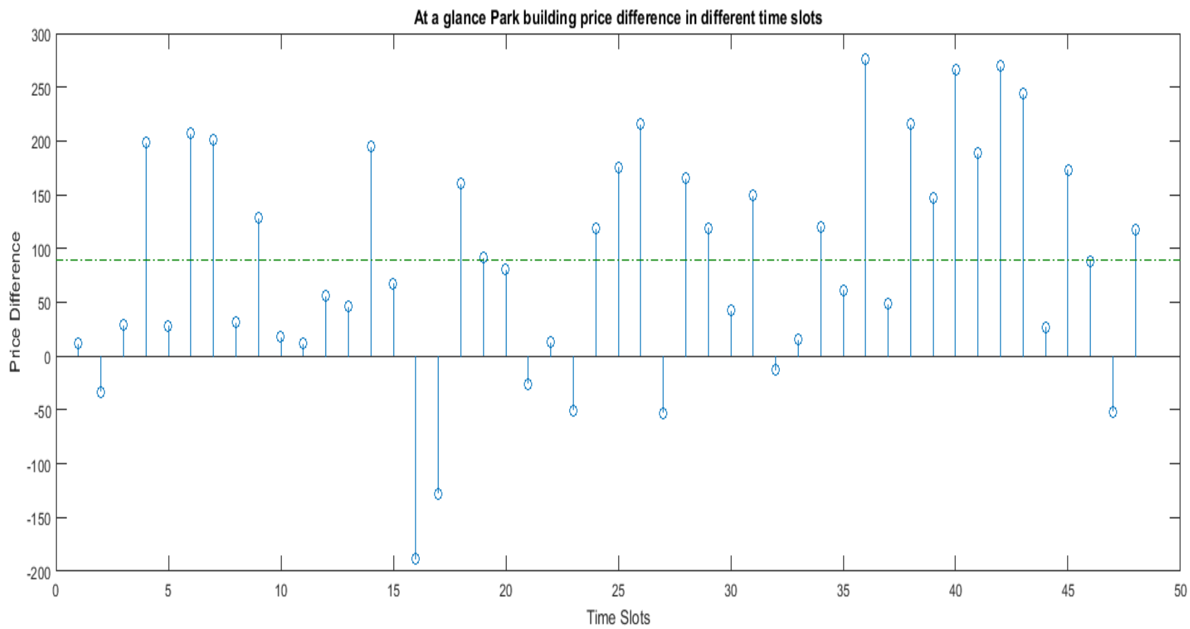

Figure 137: **Park Square building price difference in different time slots**

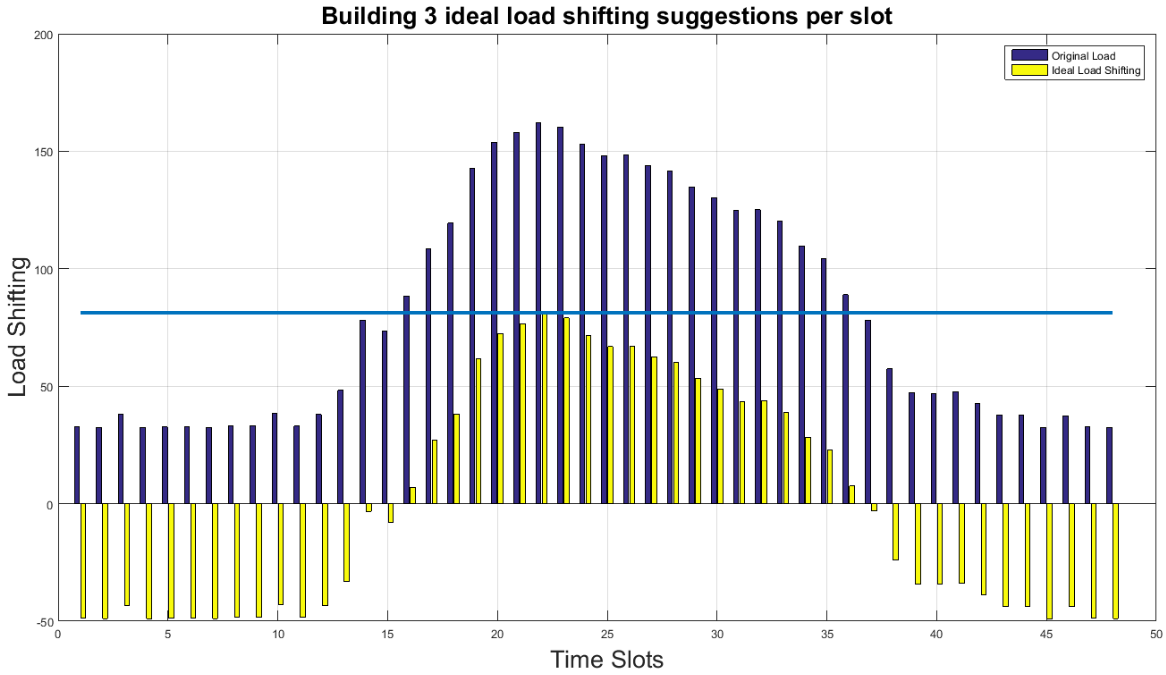

Figure 138: **Real-time ideal load shift suggestion per time slot for building 3**

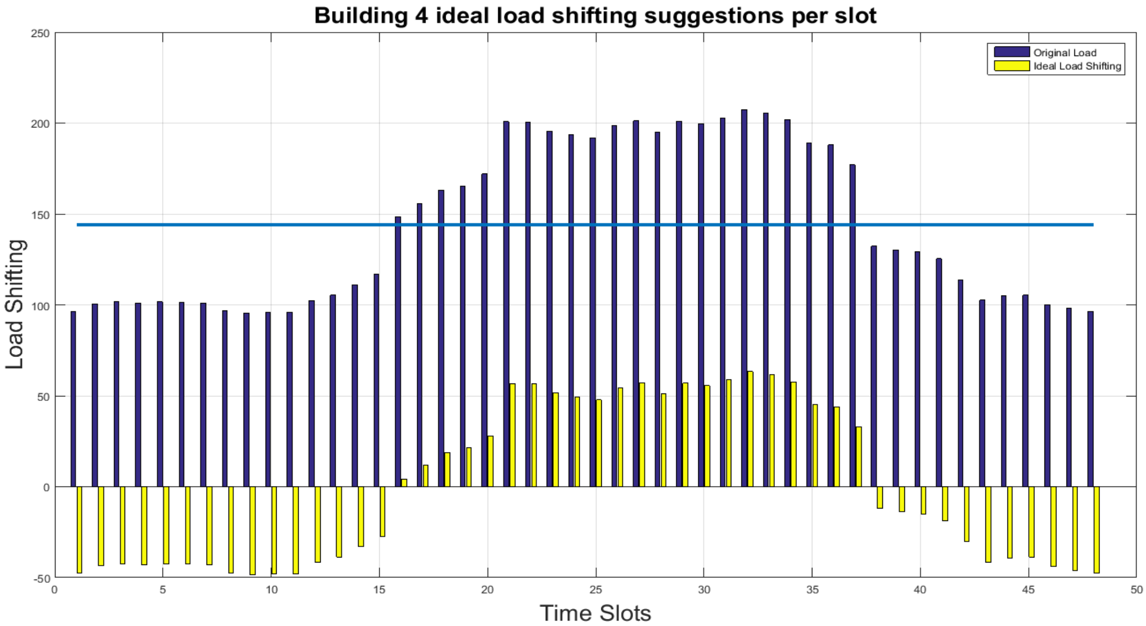

Figure 139: **Real-time ideal load shift suggestion per time slot for building 4**

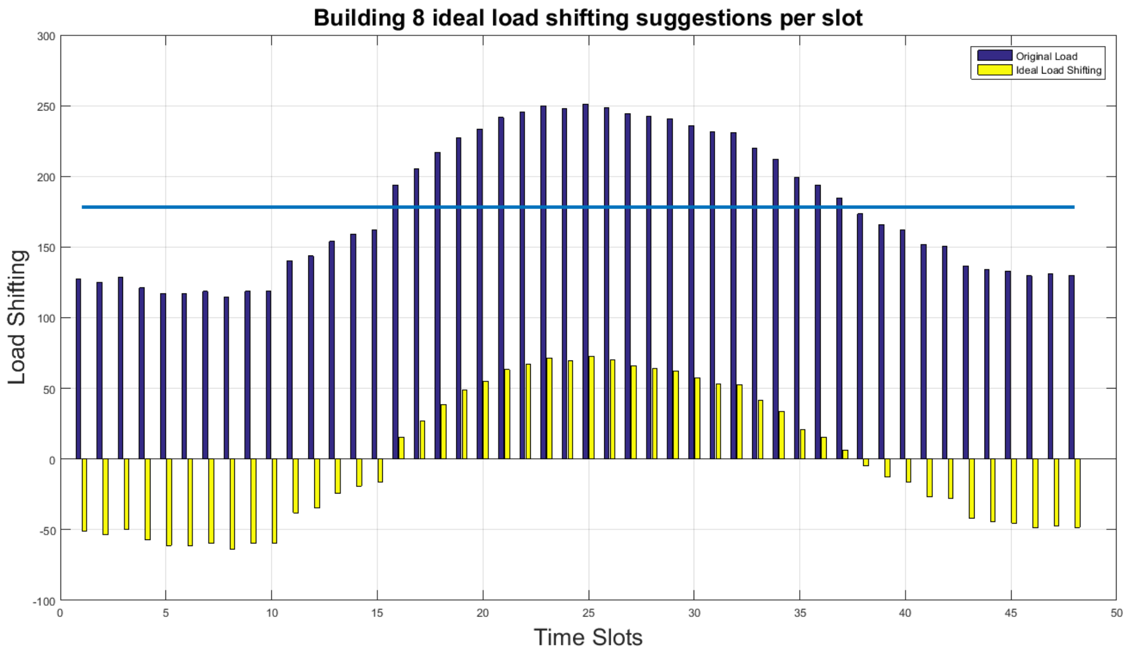

Figure 140: Real-time ideal load shift suggestion per time slot for building 8

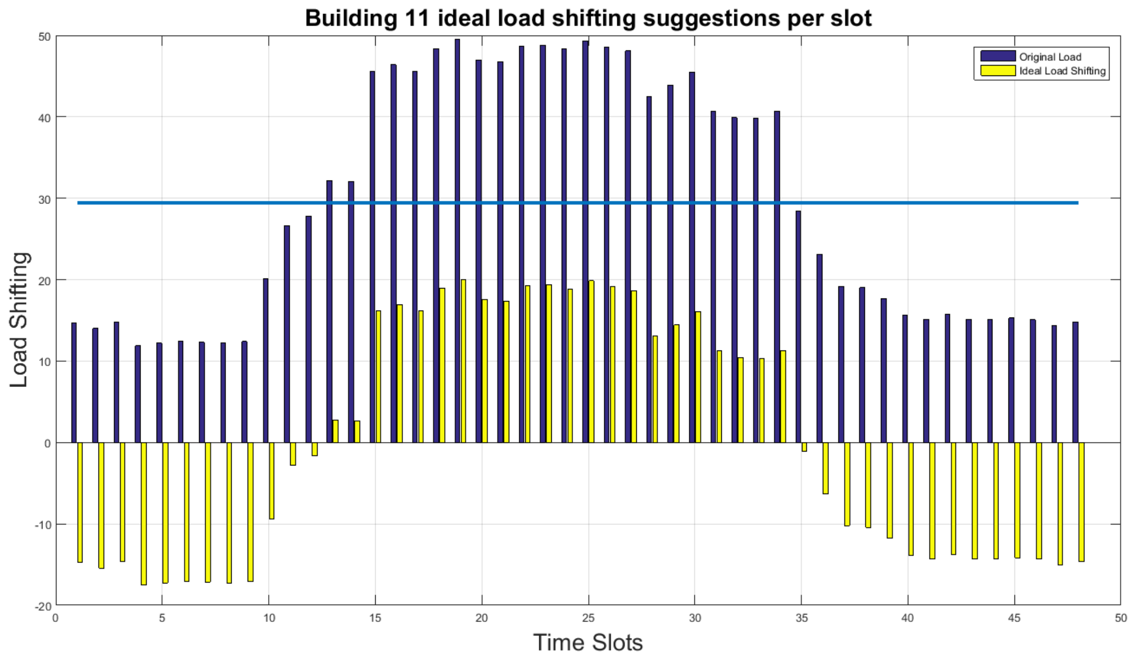

Figure 141: Real-time ideal load shift suggestion per time slot for building 11

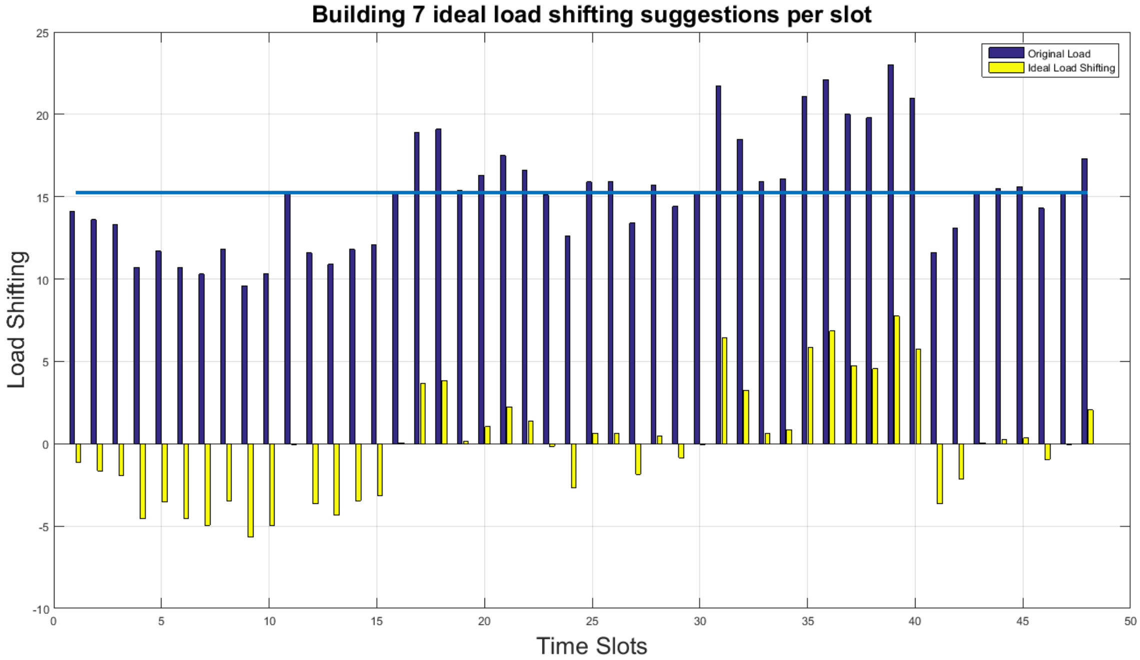

Figure 142: **Real-time ideal load shift suggestion per time slot for building 7**

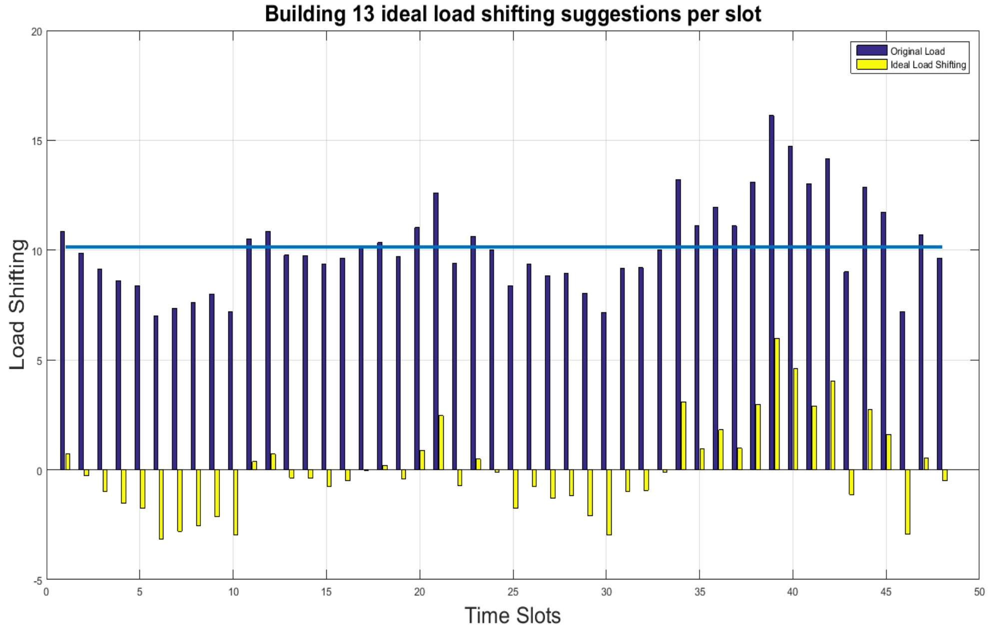

Figure 143: **Real-time ideal load shift suggestion per time slot for building 13**

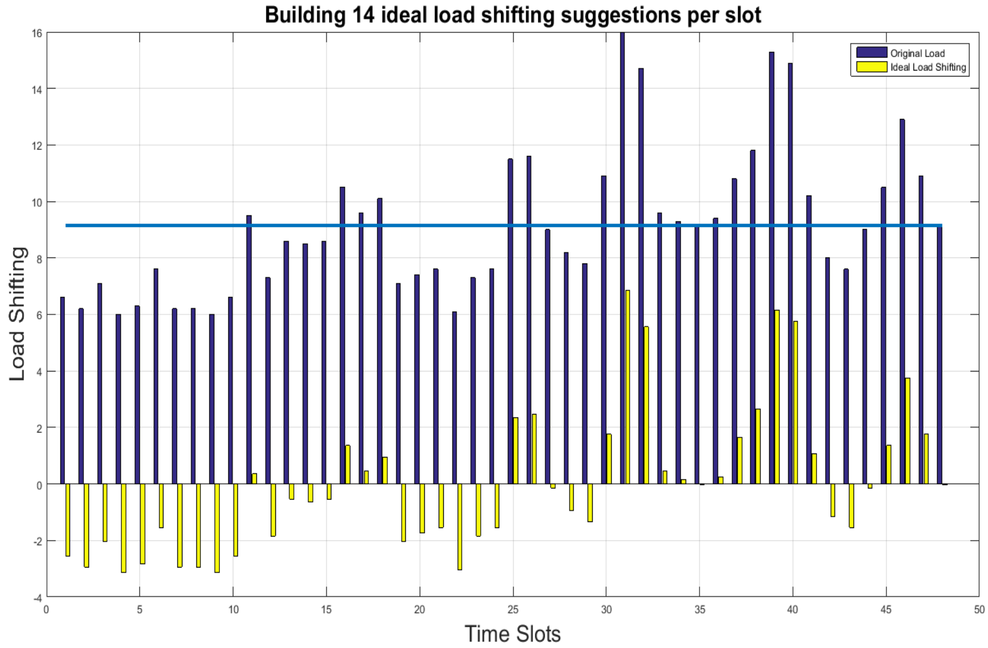

Figure 144: Real-time ideal load shifting suggestion per time slot for building 14

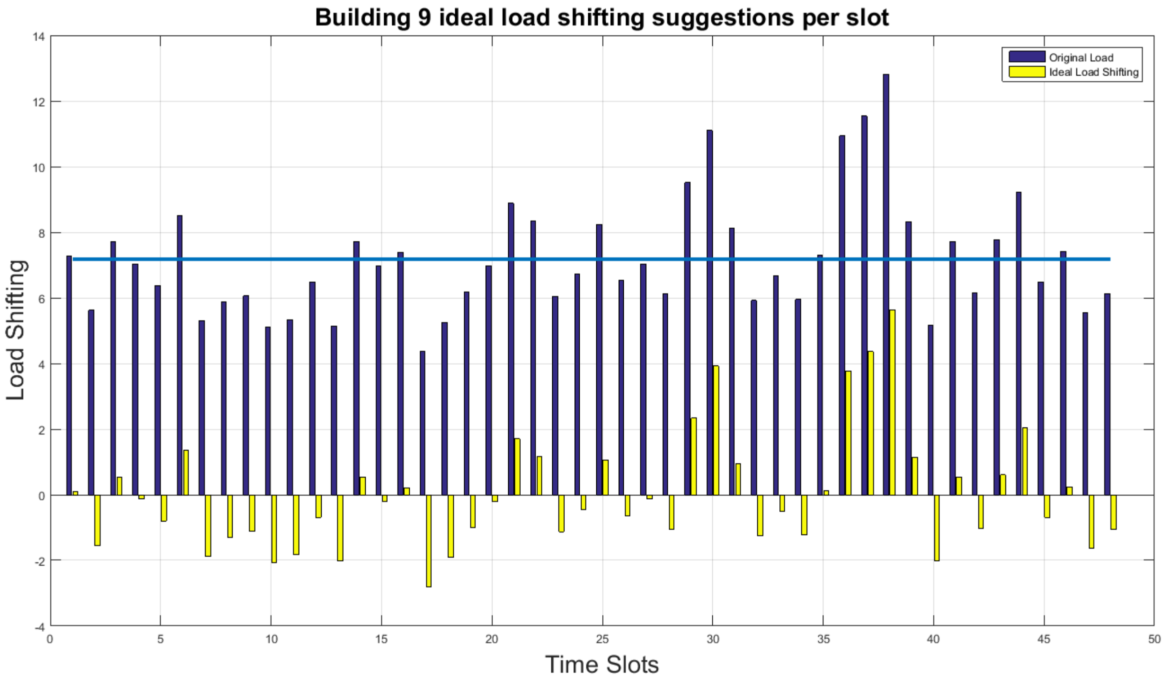

Figure 145: Building 9 ideal load shifting monthly suggestions per slot

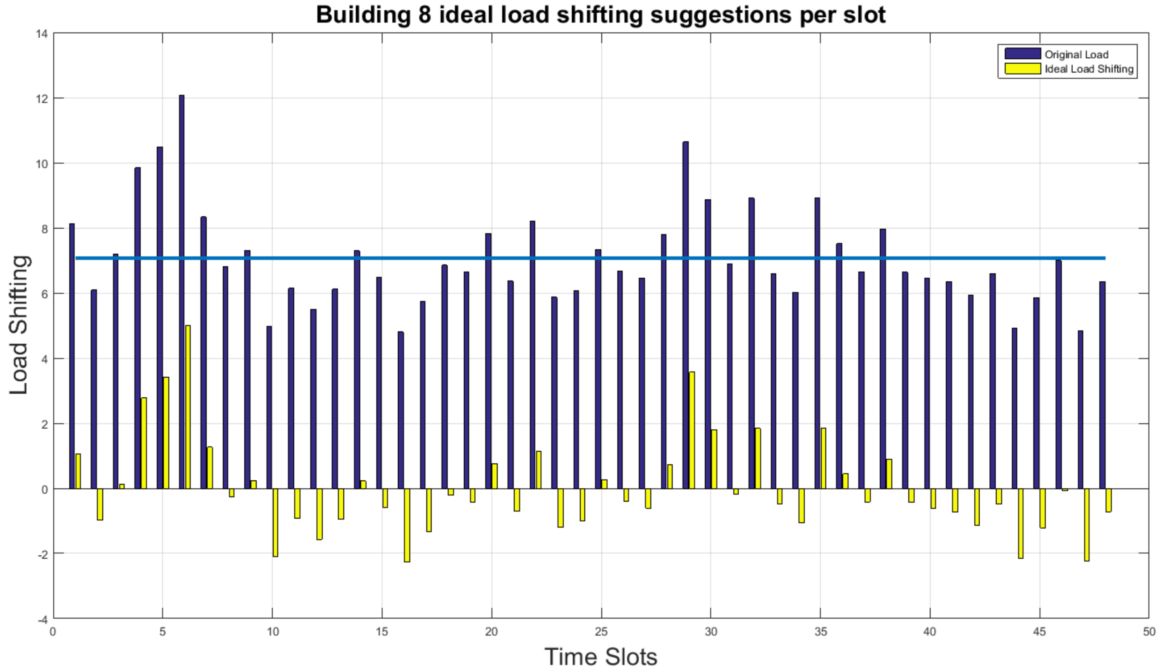

Figure 146: **Building 8 ideal load shifting monthly suggestions per slot**

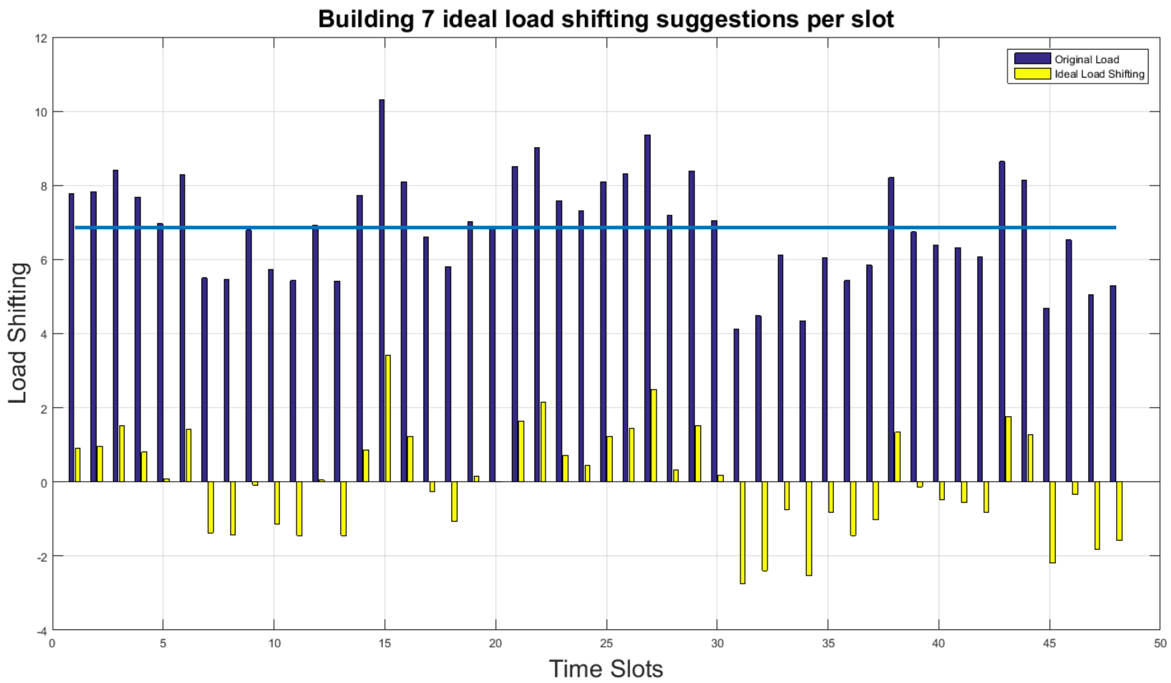

Figure 147: **Building 7 ideal load shifting monthly suggestions per slot**

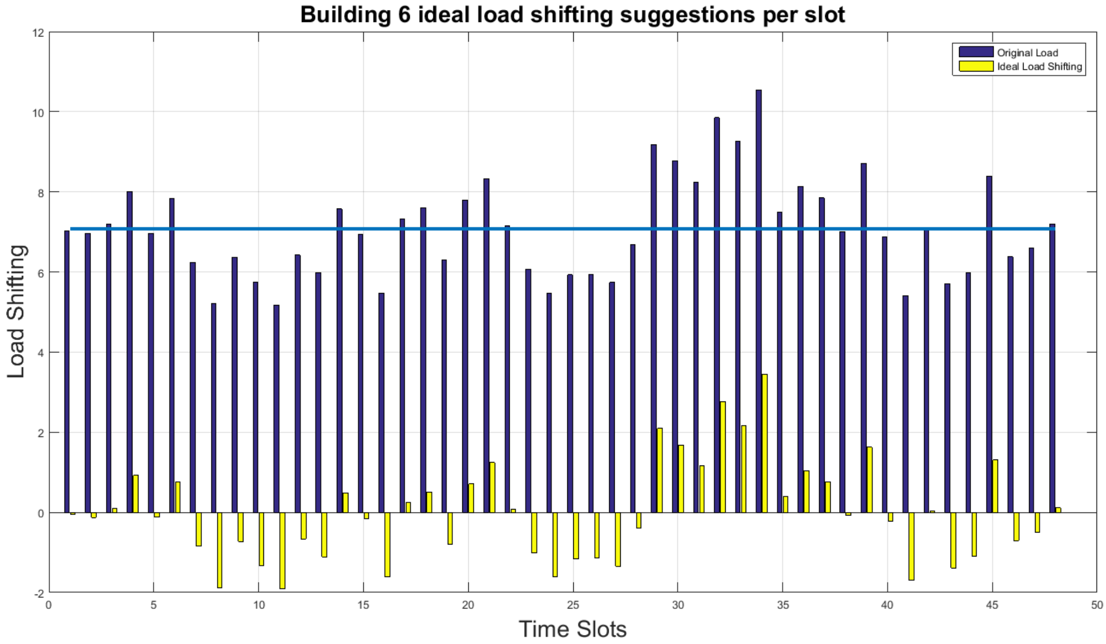

Figure 148: Building 6 ideal load shifting monthly suggestions per slot

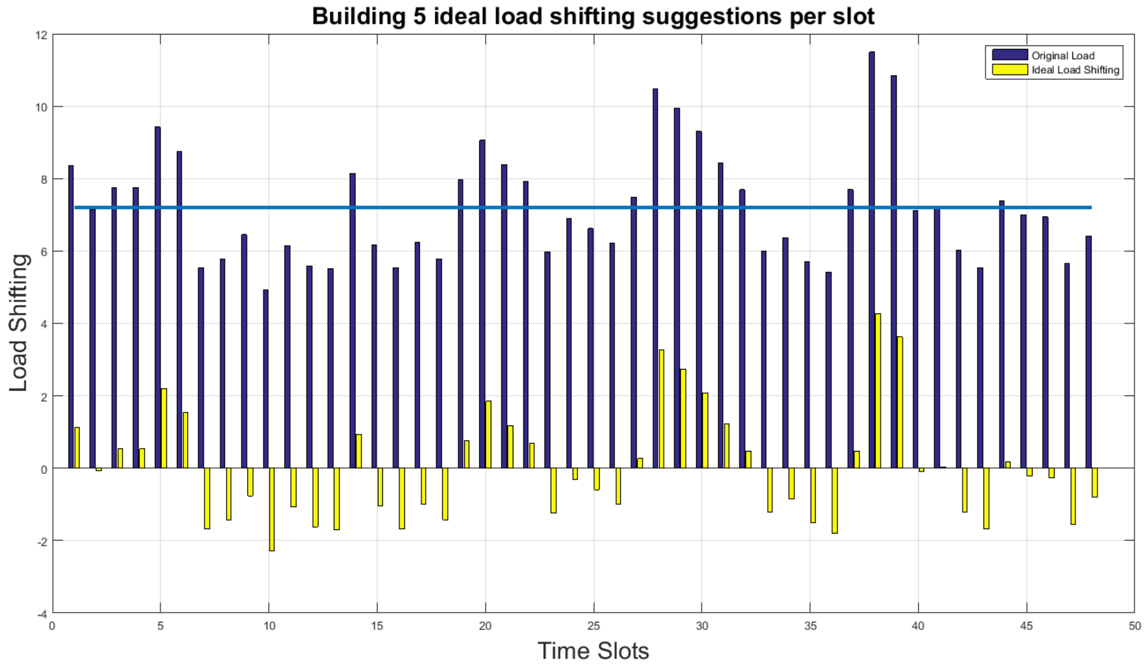

Figure 149: Building 5 ideal load shifting monthly suggestions per slot

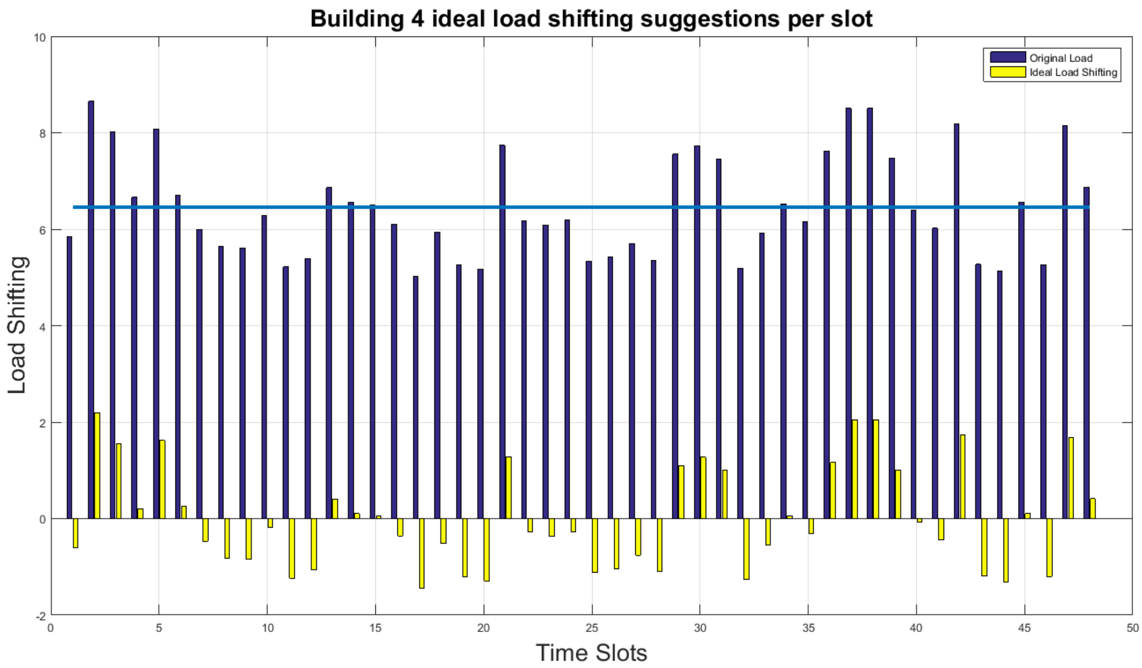

Figure 150: Building 4 ideal load shifting monthly suggestions per slot

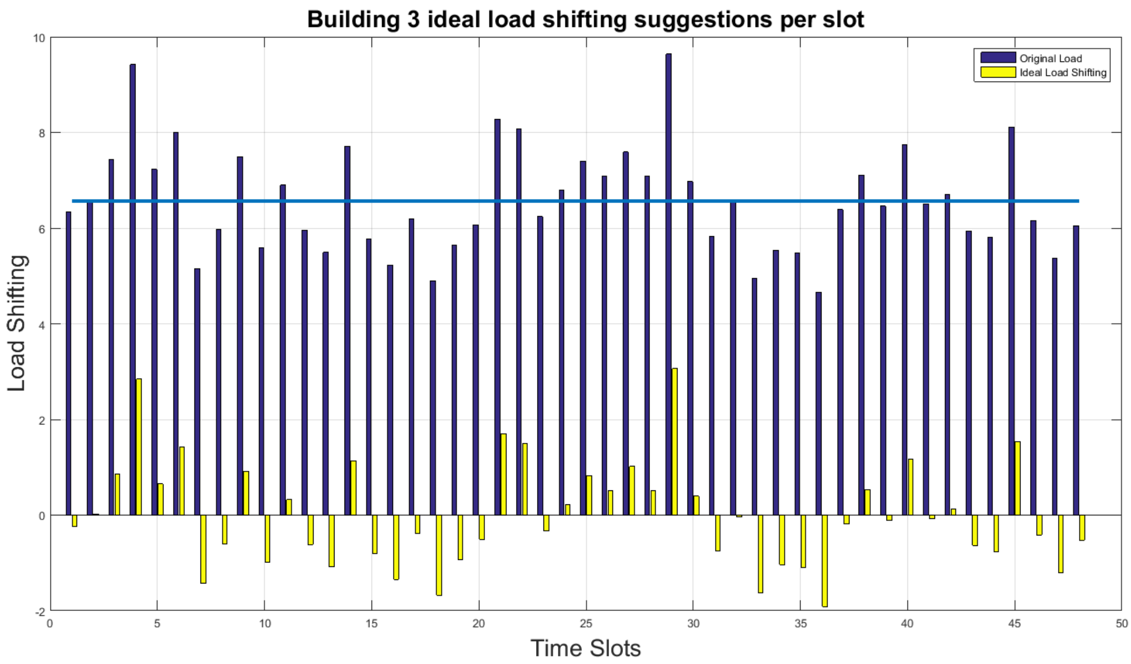

Figure 151: Building 3 ideal load shifting monthly suggestions per slot

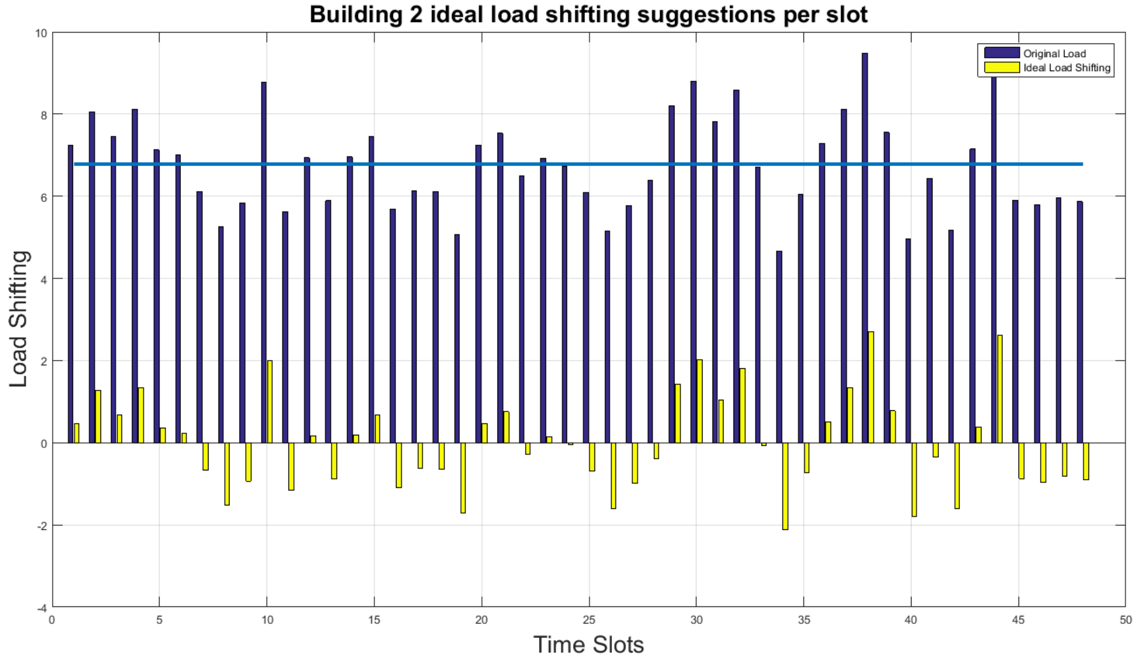

Figure 152: **Building 2 idea load shifting monthly suggestions per slot**

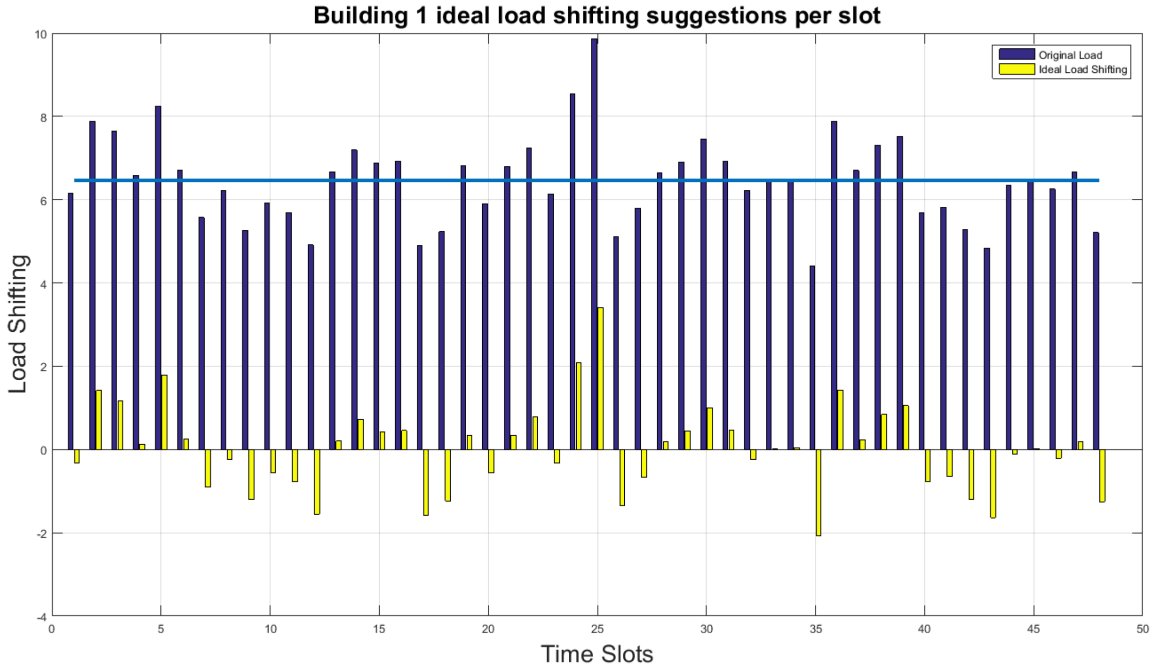

Figure 153: **Building 1 ideal load shifting monthly suggestions per slot**

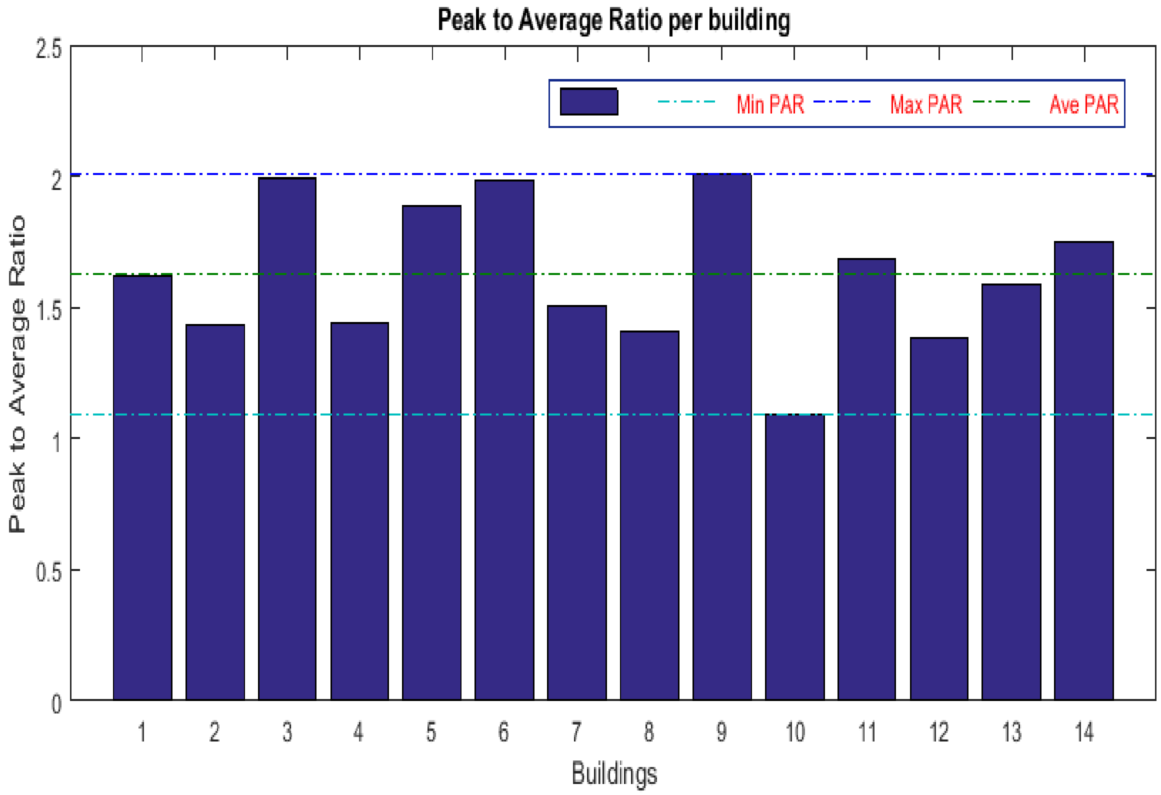

Figure 154: **Peak-to-Average Ratio (PAR) per building in general scenario**